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Christian Montag
Harald Baumeister *Editors*

Digital Phenotyping and Mobile Sensing

New Developments in Psychoinformatics

Second Edition

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ISSN 2196-6605 ISSN 2196-6613 (electronic)
Studies in Neuroscience, Psychology and Behavioral Economics
ISBN 978-3-030-98545-5 ISBN 978-3-030-98546-2 (eBook)
https://doi.org/10.1007/978-3-030-98546-2

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Foreword

It is an axiom in the business world that you cannot manage what you cannot measure. This principle, usually attributed to the business guru Peter Drucker, is equally true in medicine. Imagine managing diabetes without HbA1c, hypertension without blood pressure readings, or cancer diagnosis without pathology. Perhaps, the foundational measure in medicine was thermometry. The discovery that our subjective sense of being “chilled” accompanied the objective evidence of body temperature rising and our subjective sense of “hot” matched a fall in body temperature eliminated forever the idea that we could manage in medicine without objective measurement. We need objective data to understand and interpret subjective experience.

Unfortunately, the field of mental health has failed to benefit from the kinds of measurement that revolutionized business and medicine. While it is true that we have a century of psychological research on objective tests of cognition, mood, and behavior; little of this science has translated into clinical practice. Over the last half-century, biologically oriented researchers have followed the medical model, exploring blood, urine, and cerebrospinal fluid in the hope of finding the equivalent of HgA1c or some circulating marker of mental illness. EEG readings have been mined like EKG tracings. Brain scans and protocols for brain imaging have become ever more sophisticated in the hopes of finding the engram or some circuit dysregulation or a causal lesion. And more recently, genomics seemed a promising path to finding a biomarker for mental illness. In oncology, the most clinically useful genetic signals have proven to be somatic or local mutations in tumors, not germ line genetic variants found in blood cells which is the basis of psychiatric genetics. Nevertheless, we continue to seek causal signals in circulating lymphocytes assuming these will reflect the complex genomics of brain.

This half-century search for biological markers for mental states has been, for patients, a roller coaster of hype followed by disappointment. Thus far, science has not delivered for patients with mental illness the kind of measurement that has transformed care for people with diabetes, hypertension, or cancer. There are many potential reasons why we have failed to discover objective markers. The most common explanation is that brain and behavior are more complicated than glucose regulation or vascular tone or uncontrolled cell division. Finding the EEG signal for psychosis or the brain signature of depression will take longer. I accept this excuse, but there are three other explanations that are worth our consideration.

First, most clinicians rightly value the subjective reports of their patients as the most critical data for managing mental illness. They point out that the subjective experience of pain, anxiety, or despair is the hallmark of a mental disorder. They are not looking for quantitative, objective measures. Instead, clinicians hone skills of observation to translate their patients' reports into something more objective, usually defined by clinical terms if not a clinical numerical score. Master clinicians base their assessments not only on what they observe in the patient but on their own subjective experience, which they have learned to use as a barometer of paranoia or suicidal risk. While this approach, combining the subjective reports of the patient with the subjective experience of the clinician, might work for the provider, patients are increasingly expecting something better. Many patients realize, just as we learned from thermometry, that they cannot trust their subjective experience. Just as people with diabetes learn that every moment of lethargy is not hypoglycemia and people with hypertension learn that every headache does not mean elevated blood pressure, people with mental disorders are asking for something more objective to help them to manage their emotional states, distinguishing joy from the emergence of mania and disappointment from a relapse of depression.

A second reason for our failure to develop objective markers is that we lack a ground truth that can serve as the basis for qualifying a measurement as accurate. This is one reason why it took 200 years for thermometry to become a standard for managing an infectious disease—we had no simple proof of the value of body temperature, especially when the measure did not conform with subjective experience. Much of the clinical research on measuring biological features of mental illness has tried to validate the measure against a diagnosis. If only 40% of patients with major depressive disorder had abnormal plasma cortisol levels, then measuring cortisol could have little value as a diagnostic test. The problem here is that major depressive disorder does not represent ground truth. It is simply a consensus of master clinicians who voted that five of nine subjective symptoms constituted major depressive disorder. And none of those symptoms, including sleep disturbance and activity level, are actually measured.

For me, the most important shortcoming in our approach to measurement is that we have put the cart before the horse: We are attempting to find biological correlates of cognition, mood, and behavior before we have better objective measures of cognition, mood, and behavior. Our measures, when we make them, are usually at a single point in time (generally during a crisis), captured in the artificial environment of the laboratory or clinic, and represent a burden to both the patient and the clinician. Ideally, objective measures would be captured continually, ecologically, and efficiently.

That ideal is the promise of mobile sensing, which has now become the foundation for digital phenotyping. As described in detail in this volume, wearables and smartphones are collecting nearly continuous, objective data on activity, location, and social interactions. Keyboard interactions (i.e., reaction times for typing and tapping) are being studied as content-free surrogates for specific cognitive domains, like executive function and working memory. Natural language processing tools are transforming speech and voice signals into measures of semantic coherence and sentiment. Of course, the rich content of social media posts, search queries, and voice assistant interactions can also provide a window into how someone is thinking, feeling, and behaving. Digital phenotyping uses any or all of these signals to quantify a person's mental state.

While most of the focus for digital phenotyping has been on acquiring these signals, there is a formidable data science challenge to converting the raw signals from a phone or wearable into valid, clinically useful insights. What aspects of activity or location are meaningful? How do we translate text meta-data into a social interaction score? And how to define which speech patterns indicate thought disorder or hopelessness? As you will see in the following chapters, machine learning has been employed to solve these questions, based on the unprecedented pool of data generated. But each of these questions requires not only abundant digital data, we need some ground truth for validation. Ground truth in academic research means a clinical rating, which we know is of limited clinical value. Ground truth in the real world of practice is functional outcome, which is difficult to measure.

It is useful to approach digital phenotyping or, as it is called in some of these chapters, psychoinformatics, as a work in three parts. First, we need to demonstrate the feasibility. Can the phone actually acquire the signals? Will people use the wearable? Will there be sufficient consistent data to analyze? Next, we have the validity challenge. Does the signal consistently correlate with a meaningful outcome? Can the measure find valid differences between subjects or is it only valid comparing changes across time within subjects? Can this approach give comparable results in different populations, different conditions, different devices? Finally, we face the acid test: Is the digital measure useful? Utility requires not only that the signals are valid but that they inform diagnosis or treatment in a way that yields better outcomes. Patients will only use digital phenotyping if it solves a problem, perhaps a digital smoke alarm that can prevent a crisis. Providers will only use digital phenotyping if it fits seamlessly into their crowded workflow. As a chief medical officer at a major provider company said to me, "We don't need more data; we need more time."

Mastering feasibility, validity, and utility will also require engaging and maintaining public trust. Trust is more than ethics, but certainly the ethical use of data, consistent protection of privacy, and full informed consent about the phenotyping process are fundamental. Trust also involves providing agency to users, so that they are collecting their data for their use. There may be technical assets that can help. For instance, processing voice and speech signals internally on the phone might prove useful for protecting content privacy. The use of keyboard interaction signals, which consist of reaction times and contain no content, might be more trustworthy for some users. But it is unlikely tech solutions will be sufficient to overcome the appearance of and very real risk of surveillance. It is important, therefore, as you read the following chapters that you distinguish between the use of this new technology in a medical setting where consenting patients and families can be empowered with information versus the use of this technology in a population where monitoring for behavioral or cognitive change can be a first step down a slippery slope toward surveillance.

If we can earn public trust, there is every reason to be excited about this new field. Suddenly, studying human behavior at scale, over months and years, is feasible. Recent research is proving out the validity of this approach, already in thousands of subjects for some measures. We have yet to see clinical utility, but there is every reason to expect that in the near future, digital technology will create objective, effective measures. Finally, in mental health, we may be able to measure well and manage better. Patients are waiting.

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Preface: On the Second Edition of This Book

We are very happy to present the second edition of this book called *Digital Phenotyping and Mobile Sensing*. Immediately after the first edition has been published, we recognized that the scientific insights in this field are evolving at a rapid pace and that we also need to cover additional topics. The idea for a second edition was born. About three years of the initial publication, the updated version of this book comes to the market, now.

Within this second edition, you will find new chapters dealing with a perspective on digital phenotyping and political data science (Chap. 10, Dhawan and Hegelich) and the investigation of chat logs (Chap. 11, Kohne et al.) in Part II of the book shedding light on "Applications in Psycho-Social Sciences." Additional new chapters are included investigating Parkinsonism and digital measurement (Chap. 22, Patel et al.) and the importance to consider smart sensor technology in the health sciences (Chap. 23, Garatva et al.) as well as the development and validation of smart-sensing enhanced diagnostic expert systems aiming to assist medical experts in their decisions (Chap. 24, Terhorst et al.) or ecological momentary interventions in public mental health (Chap. 25, Schulte-Strathaus et al.). These new chapters belong to Part III called "Applications in Health Sciences."

We also appreciate that several authors chose to update their chapters (Chaps. 1, 3, 5, 7, 13, 15, 16, 18, and 19). As an exciting new feature of the book, we also present readers now with brief introductory chapters on important concepts in the realm of the present book. Please find these short chapters in our new Part IV Key Concepts.

We thank all authors who invested their time to enhance this second edition of *Digital Phenotyping and Mobile Sensing*. We appreciate their valuable contributions. Again, we also like to thank Thomas R. Insel, who revisited his foreword.

We hope you enjoy reading this new second edition of *Digital Phenotyping and Mobile Sensing* covering cutting-edge research in this timely study area.

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Contents

Chapter 1
Digital Phenotyping and Mobile Sensing in Psychoinformatics—A Rapidly Evolving Interdisciplinary Research Endeavor

Harald Baumeister and Christian Montag

Abstract In this chapter a short overview on the many topics falling under the umbrella terms digital phenotyping and mobile sensing are provided. The key terms digital phenotyping and mobile sensing are also shortly introduced. Chapter 1 is meant as a starting point to get insights on the many areas of research being covered in the second edition of this book.

Many scientists are currently considering whether we are seeing a paradigm shift in the psychosocial and behavioral health sciences from narrow experimental studies to ecological research driven by big data. At the forefront of this trend is the implementation of smart device technologies in diverse research endeavors. This enables scientists to study humans in everyday life on a longitudinal level with unprecedented access to many relevant psychological, medical, and behavioral variables including communication behavior and psychophysiological data. Although the smartphone without doubt presents the most obvious "game changer" (Miller 2012), it only represents a small part of a larger development toward the Internet of Things, where everything from household machines to the car will be connected to the Internet (Montag and Diefenbach 2018). Therefore, human interaction with all these Internet-connected devices will leave digital traces to be studied by scientists in order to predict bio-psycho-social variables ranging from personality to clinical variables including states of physical and mental health (Markowetz et al. 2014; Marengo and Montag, 2020; Marengo et al. 2022; Montag and Elhai 2019).

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*,
Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_1

The present volume gives an overview on current developments in this area, looking at digital phenotyping and mobile sensing as two prominent approaches in *Psychoinformatics*, i.e., the research field that combines innovative technological attempts with the psychosocial and behavioral health science traditions (Montag et al. 2016). Digital phenotyping extends the construct of phenotypes as the observable (biological) traits of organism to digital traces of people in a digital era of mankind (Jain et al. 2015; Insel 2017). In this context, we also hint to recent discussions about digital biomarkers (Montag et al. 2021a) and linking digital footprints to biological variables (Montag et al. 2021b). Given almost omnipresent human–machine interactions, people's digital traces might allow for diagnostic, prognostic, and intervention activities in different areas of life such as predicting product needs (e.g., by GPS tracking or bio-sensing approaches; even microtargeting (see Matz et al. 2017; Zarouali et al. 2020)), estimating personality traits, attitudes and preferences (e.g., predicting people's political orientation by social–network interaction or profile pictures (Kosinski et al. 2013, Kosinski 2021)) or improving patients health care (e.g., estimating disease and treatment trajectories based on both digital footprints and ecological momentary assessment data). Mobile sensing is the most prominent driver of this new approach, given the already substantial penetration of smartphones around the world (at the time of writing more than six billion smartphone subscriptions have been estimated (Statista.com 2022)).

Systematizing this dynamic and fast developing field of research is challenging, as technological development in diverse and unconnected research areas might already have stimulated the next wave of innovations prior to this second edition of the book being published. However, while the specific approaches might vary, a preliminary framework for using digital phenotyping and mobile sensing in psychosocial and behavioral health sciences can be proposed, as is depicted in Fig. 1.1.

A multitude of buzzwords such as machine and deep learning, big data, crowdsensing, bio-sensing, EMA, and EMI (ecological momentary assessment/intervention) are frequently used to express the impact of digitalization on people's lives and on societies as a whole. Note that we use the term *digitalization* here, because it describes how the use of digital technologies shapes society (or here scientific research), whereas digitization refers to the mere process of transforming analog into digital data.

Mobile sensing is often specified by the device providing the mobile sensing data, i.e., smart sensing devices such as smartphone, smartwatch, and smart-wearables, and by the data a smart sensing device is tracking, e.g., voice and speech sensing, bio-sensing, passive sensing, crowdsensing, and ecological momentary assessment or facial emotion recognition sensing. Using these terms already stimulates our imaginations regarding both risks and potentials associated with this still new technology, capable of altering peoples' and societal life to a degree that has not yet been fully grasped.

Digital phenotyping constitutes one relevant application in the area of mobile sensing, with the potential to substantially improve our knowledge in the realm of latent constructs such as personality traits and mental disorders (Montag et al. 2021c). A better understanding of these variables is of great relevance, because personality

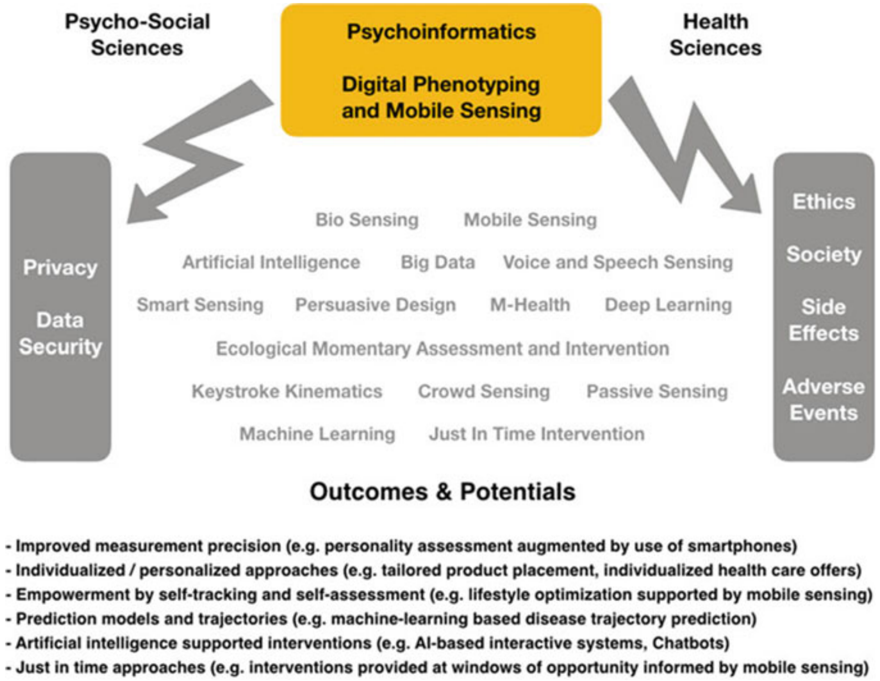

Fig. 1.1 Digital phenotyping and mobile sensing conceptual framework

traits such as conscientiousness are good predictors for a healthy living style (Bogg and Roberts 2004; but also see for cultural effects Kitayama and Park 2021) and mental disorders are a tremendous source of individual suffering and high costs for society (Trautmann et al. 2016, Health 2020). At the same time, digitally supported health care offers seemingly are capable of improving mental and behavioral health (Ebert et al. 2017, 2018; Bendig et al. 2018; Paganini et al. 2018).

Our life has become digital and this digital image of our lives and persons can be ephemeral or used to provide the data basis necessary to estimate people's traits, states, attitudes, cognitions, and emotions (Montag and Elhai 2019; Marengo et al. 2022; Martinez-Martin et al. 2018; Lydon-Staley et al. 2019). What does your smartphone usage pattern tell us about you and your state of mind? What does your vacation, social, and work life pictures posted in social networks tell us about your happiness and your attitude toward work, holiday time, and your spouse? Would we recognize a change in mental state when comparing voice recordings from today and 5 years ago? What will your lunch look like tomorrow? You might not know it, but maybe your bio-sensing signals will tell us now already. Two advances enable us to provide increasingly sophisticated digital phenotyping estimates: Big Data and machine/deep learning approaches.

Big Data constitutes a precondition for digital phenotyping based on a granular matrix of our digital traces, consisting of a multitude of (longitudinally) assessed variables in large cohorts coming at different degrees of velocity (speed), variety (data format), and volume. In short, Big Data can be described by varying degrees of VVVs (Markowetz et al. 2014). Once those databases have been established, we are confronted with a large set of complex data for which established statistical methods are often not the best fit.

Machine learning and deep learning (ML/DL) are the buzzwords that promise to make sense out of the big data chaos (Lane and Georgiev 2015; but see how psychological theories can guide machine learning principles, Elhai and Montag 2020). While some rightly argue for a more well-thought through scientific basis in the current machine learning hype (Kriston 2019), these analytical approaches are undoubtedly the key for the last puzzle of digital phenotyping and mobile sensing covered in the present volume: artificial intelligence (AI). This said, ML as an integral part of AI comes with many problems such as a lack of understanding of what kind of patterns the computer actually recognizes or learns when predicting a variable such as a tumor from an MRI scan (Mohsen et al. 2018). Aside from this, a demanding topic is that of programming ethics into deep learning algorithms (the field of machine ethics, see in, e.g., Moor and James 2006; Brundage 2015).

Artificial intelligence (AI) might become central to several fields of application, by pattern recognition using deep learning algorithms (Ghahramani 2015; Topol 2019). For instance, in a first development step, users of AI-based medical programs will be supported in interpreting diagnostic results and receiving AI-based prognostic feedback regarding the current treatment course of their patients. Predicting economic or environmental impacts of political decisions and tailoring product placement according to peoples' personality based on AI algorithms are further likely fields of application (but see also limits in prediciting for instance voting behavior from self-reported Big Five traits with machine learning; Sindermann et al. 2021). Once developed, these artificial intelligence applications might again use mobile sensing techniques to further improve their prognostic power by means of a deep-learning-based self-improvement cycle (see Fig. 1.2).

The chapters of this book provide a snapshot of what is already possible and what science might allow in the near future. Thus, most chapters not only focus on the areas of applications and the potentials that come along with these approaches but also on the risks that need to be taken into account, principally in terms of data privacy and data security issues as well as ethical and societal considerations and possible side effects of mobile sensing approaches. In this context also a recent opinion article is relevant stressing how to increase benefits and to reduce harm in the area of digital phenotyping (Montag et al. 2020). Regarding the risks, chapters by Kargl and colleagues (Chap. 2), who provide an overview of privacy issues as inherent aspect of mobile sensing approaches, and by Dagum and Montag (Chap. 3), who reflect on ethical implications of digital phenotyping, consider the ethical boundaries of our actions. Examples of unintended de-anonymization of data summarized by Kargl et al. (Chap. 2) shows how easily supposedly anonymized data can quickly become person identification data when combined with the almost infinite information on everything and everyone in our Internet of Things world. Answers on these ethical questions need a scientific discourse on how to exploit the potential of mobile sensing

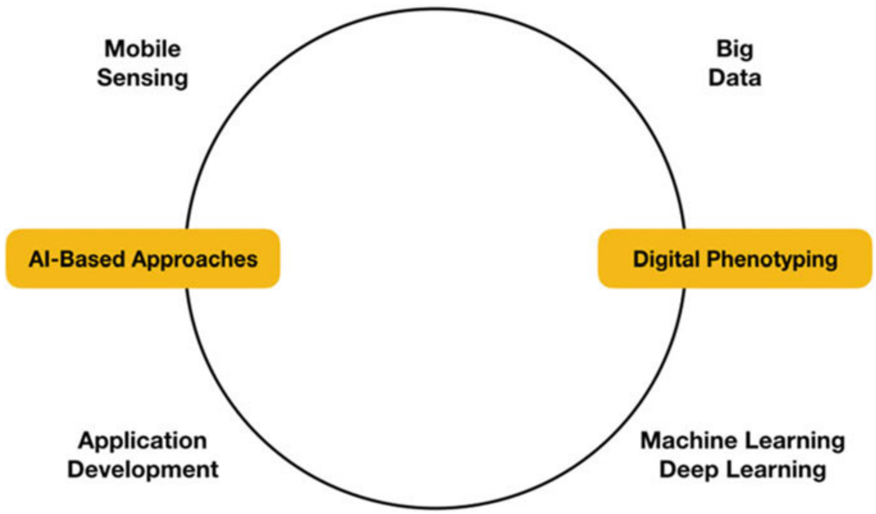

Fig. 1.2 Mobile sensing, digital phenotyping, and artificial intelligence life cycle

in an ethical way but also a societal discourse on what we are willing to accept in light of the conveniences mobile sensing approaches provide (e.g., accepting that Google knows where we are as a trade-off for using Google maps to navigate through traffic or find our ways in unknown places).

With these privacy and ethics boundaries in mind, readers of this book are provided with a look into the future that is already happening.

Several chapters provide exemplary research and conceptualization frameworks on mobile sensing approaches across the psychosocial and behavioral health sciences fields. Digital phenotyping, mental health prediction models, ecological momentary assessments, insights from political data science and academic performance estimates (Cao, Gao, and Zhou: Chap. 9; Kubiak and Smyth: Chap. 15; Dhawan and Hegelich: Chap. 10; Kohne, Elhai and Montag: Chap. 11; Marengo and Settanni: Chap. 8; Rozgonjuk, Elhai and Hall: Chap. 14; Sariyska and Montag: Chap. 5; Schlee et al.: Chap. 16; Vaid and Harari: Chap. 6) are only some of the possibilities in the realm of mobile sensing discussed in this book. The chapters range from established fields of mobile sensing that can already draw on empricial evidence (Jacobson et al. 2019; Jagesar et al. 2021; Saeb et al. 2015; Sariyska et al. 2018; Montag et al. 2019), such as predicting personality or mental and behavioral health status by means of smartphone usage patterns to less established fields such as the potential of bio-sensing, which might allow in future such things as physiologically delineated measures to improve health (e.g., cortisol implants measuring stress-related symptoms that could inform a mobile health application to provide a just-in-time intervention). In this context, we again hint towards the discussion around digital biomarkers (Montag et al. 2021a).

A second group of chapters focuses on the potential for machine learning and deep learning approaches. Geiger and Wilhelm (Chap. 4), for example, illustrate the research potentials of combining mobile devices with face recognition software allowing for immediate facial emotion expression recognition based on machine learning algorithms (see also Marengo et al. 2022). Similarly, Hussain and colleagues (Chap. 13) reflect on the potential of machine-learning-based keyboard usage and corresponding typing kinematics and speech dynamics analysis for predicting mental health states. Regarding speech-analysis-based machine learning approaches, Cummins and Schuller (Chap. 12) present a selection of already available open-source speech analysis toolkits along with a discussion on their potentials and limitations.

Several chapters provide frameworks and insights into how these fields of research can be used and combined to inform complex intervention developments in order to further improve people's health and living. While Messner and colleagues (Chap. 18) report on the current state of research regarding mHealth Apps and the potential that comes with new sensing and AI-based approaches, Pryss and colleagues (Chap. 19) present a framework for chatbots in the medical field. While most of the current chatbot approaches are based on a finite amount of answer options the chatbot can access (Bendig et al. 2019), the framework presented in this chapter looks at how the expert knowledge database necessary for complex communication situations such as psychotherapy can be generated and iteratively improved until a truly artificial intelligent chatbot therapist is at place. Baumeister et al. (Chap. 20), with a focus on persuasive-design-based intervention development, and Rabbi et al. (Chap. 21), with a model for just-in-time interventions, provide further details on how technology can be used to further improve existing interventions, enhance intervention uptake and adherence, and ultimately increase effectiveness by exploiting the full potential of mobile sensing. In Chapter 22 an outlook on Parkinsonism and digital phenotyping is presented, Chapter 23 deals with smart sensors in health research and Chapter 24 provides an overview on diagnostic expert systems being enhanced by smart sensing technologies. Chapter 25 sheds light on ecological momentary interventions in the context of public mental health provisions. The book closes with six short definition chapters providing an accessible and quick introduction into relevant core concepts of the book (Chapters 26–31). We refrained from doing such chapters on mobile sensing and digital phenotyping, as this would be redundant with this and other chapters.

Writing these few paragraphs on the content of the second edition of our book fills us with excitement about the perspectives digital phenotyping and mobile sensing offer for research and practice. At the same time, however, we feel uneasy in light of the obvious risks for individuals and society at large. Researchers should not usually argue based on their emotions, but in this case these two emotions—positive and negative—might guide the next steps by a development process for future innovations that is ethical and informed on issues of privacy. It therefore seems that the development of new technical solutions will take place anyway given their potential economic value, leaving research to establish conceptual frameworks and guidelines to set the guardrail. Focusing on the example of artificial intelligence, large-scale companies will probably revolutionize the product market with ever more intelligent systems, increasing the convenience of consumers and at the same time reducing human workforce needs. However, these companies will probably not provide the urgently needed answers on how to develop and implement such innovations in a way that benefits society (Russell et al. 2015) considering all the scenarios relating to potentially malevolent AI (Pistono and Yampolskiy 2016; see also some visionary thoughts in Kai Fu Lee's 2018 book). Broadening the focus again, we need to establish good scientific practice for mobile sensing in order to exploit its full potential (see also Montag et al. 2020). Scientists currently discuss whether the paradigm shift postulated at the beginning of this editorial needs to undergo fine-tuning, setting the ecological correlation research approach into the context of explorative and explanatory research paradigms. Exploratively fishing for hypotheses is the beginning and not the end of methodologically sound psychosocial and behavioral health science (Kriston 2019).

This said, at the end of this short introduction we want to express our gratitude to all our authors for their important chapters of the second edition of this book. They all invested a lot of their time and energy to provide insights into their different research perspectives.

We have not mentioned so far that Thomas Insel, former director of the National Institute of Mental Health (NIMH) in the USA and a prominent advocate of the digital phenotyping movement, was kind enough as to provide us with his thoughts on this relevant research area. We also mention his new book called "Healing" reflecting on what's really important to deal with the mental health crisis (Insel 2022). Hopefully, digital phenotyping and mobile sensing procedure can be an effective supplement to achieve this ambitious goal.

Conflict of Interest Christian Montag mentions that he received funding from Mindstrong Health for a project on digital phenotyping. Beyond that he serves as scientific advisor for Applied Cognition, Redwood City, CA, USA. This activity is financially compensated.

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Part I
Privacy and Ethics

Chapter 2
Privacy in Mobile Sensing

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Abstract In this chapter, we discuss the privacy implications of mobile sensing used in modern psycho-social sciences. We aim to raise awareness of the multi-faceted nature of privacy, describing the legal, technical and applied aspects in some detail. Not only since the European GDPR was introduced, these aspects lead to a broad spectrum of challenges of which data processors cannot be absolved by a simple consent form from their users. Instead appropriate technical and organizational measures should be put in place through a proper privacy engineering process. Throughout the chapter, we illustrate the importance of privacy protection through a number of examples and also highlight technical approaches to address these challenges. We conclude this chapter with an outlook on privacy in mobile sensing, digital phenotyping and, psychoinformatics.

2.1 Introduction

While mobile sensing provides substantial benefits to researchers and practitioners in many fields including psychology, the data collected in the process is often sensitive from a privacy perspective. Data collected by smartphones and other devices with sensors, such as fitness trackers, is clearly related or relatable to persons. Therefore, the researcher or practitioner that collects, processes, and stores such data has moral and frequently legal obligations to handle this data responsibly. This is especially important if the data is related to health or mental disorders of a person.

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*,
Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_2

The right to protection of personal data has been recognized as a central human right and is, for example, embedded in the European Charter on Human Rights.[1] In this chapter we want to raise awareness of the importance of privacy and data protection in the context of mobile sensing. To this end, we introduce privacy from a legal, technical, and applied perspective, as well as discuss some of the associated challenges. In particular, we want to dispel the myth that a consent form from a study participant relieves the researcher from all legal data protection obligations. Beyond legal obligations, we discuss some evidence that a lack of privacy may negatively affect the participants' or patients' trust in systems or procedures. Finally, we provide a positive outlook on how both the legal and ethical obligations in mobile sensing application could be achieved by proper privacy engineering and the application of privacy-enhancing technologies (PETs).

Privacy protection has already been recognized as an important issue within the psycho-social research community after controversial incidents such as the Tearoom Trade study by Humphreys. The name of the study refers to male-male sexual behavior in public bathrooms. In his work, Humphreys not only surveyed unwitting subjects in extremely private and intimate situations (sexual intercourse in public bathrooms) without their consent, he also collected personally identifiable data (license plates) to later de-anonymize the subjects and visit their homes under false pretenses for follow-up interviews. This study demonstrated the fatal effects when personal data is collected in studies without any regard to privacy (Kelman 1977).

One of the first to investigate weaknesses in anonymization of health data was Sweeney (Sweeney 2002), who showed that anonymized hospital discharge records contained sufficient information to de-anonymize many patients when matching zip code, gender, and date of birth information included in the records to publicly available US census data. Further examples (Boronow et al. 2020; Gymrek et al. 2013; Homer et al. 2008) lead to the conclusion that proper anonymization becomes extremely hard if the opponent has sufficient context knowledge.

De-anonymization is also an issue for location privacy and other data collected by mobile devices such as smartphones and fitness trackers. For example, the fitness tracking company Strava released data from its service, where many people uploaded GPS-tagged traces from their daily runs. People analyzing this massive data set quickly found out that it included runs from soldiers in supposedly undisclosed military bases.[2] Similarly, anonymous trip records published from New York taxis have been used to identify trips by celebrities and find out whether they tipped the driver or not.[3] Such examples have led to the conclusion that strong anonymization is really hard and the category of personal identifiable information (PII) needs to be broadened up substantially. This is also reflected in the modern understanding of privacy and current lawmaking, such as the European General Data Protection Regulation (GDPR) that expands the scope of PII and stresses the importance of careful privacy-by-design.

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[1] http://www.europarl.europa.eu/charter/pdf/text_en.pdf.

[2] https://www.theguardian.com/world/2018/jan/28/fitness-tracking-app-gives-away-location-of-secret-us-army-bases.

[3] http://content.research.neustar.biz/blog/differential-privacy/QueriesWidget.html.

2.2 Privacy as a Multifaceted Concept

2.2.1 Privacy as a Legal Concept

Many countries have regulated different aspects of privacy in their laws. Legal protection of personal data is termed data protection. One of the most holistic data protection frameworks is the European General Data Protection Regulation (GDPR), which is applied throughout Europe since 2018 and which unified the previously differing data protection regimes throughout Europe.

While it is beyond the scope of this chapter to provide a complete overview of the GDPR, we still use it here to illustrate major concepts of data protection. GDPR, or "Regulation (EU) 2016/6791" as it is officially named, regulates the *processing* of *personal data* relating to a natural person in the EU, by an individual, a company or an organization. As described in Article 4, *personal data* includes data that is indirectly related to a person, while *processing* has to be understood to also include activities such as collection or storage of personal data.

The GDPR places many requirements on anyone that either conducts data processing (termed "data processor") or is responsible for data processing (termed "data controller"). In addition, "data subjects", which are the natural person(s) to whom the data relates, are given a broad set of rights, such as the right to be informed or the right to erasure of the processed data. Any processing of personal data requires a legal basis, where GDPR names a *legal requirement*, *fulfillment of a contract*, or *informed consent* of the data subject among others. In psychological studies, such informed consent is typically the basis for processing of personal data, also also *public interest* in the research may be argued. However, neither consent nor public interest will free the data controller or processor from the broad set of obligations that come with the right to process personal data (Schaar 2017). These obligations include the information rights of data subjects, such as the right to be informed, the right to access such data in a portable format, and the right to object to data processing, even after the fact. This obviously clashes with some obligations of researchers on research data management or concepts from Open Science like archiving and sharing of data to enhance reproducability.

In this chapter, we want to focus on yet another aspect of the GDPR: Privacy by Design (PbD) and Privacy by Default. In particular when processing sensitive data or in high-risk cases, the GDPR mandates any system that processes personal data to be designed privacy-friendly from the ground up. This should be achieved by following a PbD design and development process based on a Data Protection Impact Assessment (DPIA) that investigates potential privacy issues right from the start. Privacy by Default implies that system configuration should default to the most privacy-friendly setting and users should have to opt-in for less protection. The GDPR further requires that state-of-the-art technical and organizational measures (TOMs) be integrated into the foundations of such a system. However, even some years after introduction of GDPR it is still not fully clear how "state-of-the-art" is to be defined precisely.

All these aspects have substantial implications on how psychological research can be conducted in a legally safe way. In the remainder of this chapter, we will first illustrate these consequences and then address how such privacy and data protection may be achieved. Finally, we will discuss how we see modern privacy engineering processes and technologies can help to conduct research in psycho-social research in a compliant and responsible way.

2.2.2 Privacy as a Technical Concept

In technical literature, privacy is often defined in a quantifiable way, for example through a anonymity set or information-theoretical measures like Shannon entropy as this greatly simplifies the analysis of technical solutions employed to protect privacy. The simplest conception of privacy in the technical literature is anonymity, which means that "a subject is not identifiable within a set of subjects, referred to as the anonymity set" (Pfitzmann and Hansen 2010). The anonymity set of a subject is the set of subjects that have the same properties (e.g., age category, gender, disease characteristics) so that one cannot distinguish one particular person from the others in the group. If the total data set considered is a database published as research data, removing direct identifiers like names or pseudonyms of subjects may not be enough to achieve anonymity, since each subject may have other (combinations of) properties that identify him or her uniquely. Such indirectly-identifying attributes are called quasi-identifiers. If, however, a data entry from one person is not distinguishable from $k - 1$ others through (quasi-)identifiers, we call that person k-anonymous within the database. Another related but distinct concept is that of linkability, which is given if for "two or more items of interests (e.g., subjects, messages, actions, …) […], the attacker can sufficiently distinguish whether these are related or not" (Pfitzmann and Hansen 2010). This is a stronger requirement than that of anonymity, since knowing whether two messages originate from the same source does not (necessarily) identify the source. However, in many cases, linkability of messages implies the possibility of de-anonymization. For example, in the location privacy example of New York taxis above, linkability of locations led to de-anonymization of individuals, as explained by Douriez et al. (2016).

To design and validate practical privacy enhancing technologies (PETs), researchers also apply such privacy metrics to quantify the privacy a specific PET can provide. To this end, many different metrics were developed (Wagner and Eckhoff 2018) to quantify, for example, how anonymous a subject is within their anonymity set. Often, the challenge is that the analysis is conducted in a closed system context while many attacks rely on additional external information sources to perform a de-anonymization of seemingly anonymous data.

To overcome related problems, many types of ever more sophisticated metrics were developed, where most prominent ones can be categorized into data similarity (where k-anonymity is a widely-known example) and indistinguishability (where differential privacy is a prominent example). We refer interested readers to Wagner and Eckhoff (2018) for a detailed survey of these metrics. Privacy research in recent years has thus provided a much refined understanding of privacy and provided new mechanisms to breach but also to better protect privacy. This can be leveraged to support the ever more data-driven research in psychology and mobile sensing to not infringe personal privacy in an ever larger degree.

2.2.3 Privacy as a Concept in Research Studies and Treatments

In the context of research studies, experiments, and treatments related to healthcare and psychological well-being, privacy is particularly relevant from two perspectives. First, the protection of data from participants or patients raises strong obligations for researchers or therapists, as the ethical principles in these professions go even beyond the legal requirements. Second, the participants' or patients' perception of their privacy influences their trust in the procedure, which can potentially even negatively affect the results or the outcome of the study or treatment.

Organizations such as the American Psychological Association (APA) take into account privacy obligations as part of their ethical principles. For instance, section four of the APA Ethics Code specifically addresses privacy and confidentiality, requiring that the confidentiality of collected information is maintained, as well as the minimization of privacy intrusions. Best practices have been established to adhere to these principles in traditional settings (e.g., usage of pseudonymization codes). However, novel approaches such as mobile sensing and smartphone-based data collection, entail new threats to privacy and confidentiality, which cannot be addressed with existing practices alone. In consequence, an increasing technologization of experiments and treatments requires equal advancements in the safeguarding and (technical) enforcement of ethical principles.

Orthogonal to the ethical considerations, addressing the privacy concerns of participants and patients has a positive impact on the procedure outcome. According to a model of Serenko and Fan (2013), informational privacy (i.e., information acquisition and ownership) has the strongest influence on a patient's privacy perception in the healthcare context. The level of perceived privacy is associated with the level of trust of the patient in the treatment. Again, this trust level is associated with the behavioral intentions of the patient such as commitment, adherence, and compliance with the treatment. Furthermore, ensured anonymity and confidentiality in studies work against the social desirability bias (Krumpal 2013)—a tendency to give answers that are considered to be favorably by other peers. Joinson (1999) found similar effects in early, web-based questionnaires.

On the other hand, recent developments in psycho-social research have shown many results were not reproducible by further studies. This has given rise to the open science movement, whose primary goal is to improve reproducibility through data availability. A wide variety of data management platforms, such as the Open Science

Framework (https://osf.io) and Zenodo (https://zenodo.org), have risen in this context, whose primary aim is to widely disseminate research data. However, sensitive personal data clearly cannot be published in this fashion under the GDPR regime; technical solutions are required to ensure that the data is used only in correspondence with the consent provided by the user, under the obligations posed by the GDPR.

As we have shown, privacy is a complex and challenging concept for data processing in human subject research from many perspectives. New technological developments like mobile sensing aggravate these challenges even more. We now continue to refine these challenges in more detail before discussing possible technical solutions.

2.3 Challenges in Privacy

While mobile sensing enables new forms of participatory research and discovery by collecting almost endless amounts of sensor data about human activities and derivable behavior, such systems create distributed and massive databases of patients or participants data and maybe even of unrelated people in the surrounding. This collection and processing of large amounts of sensor data leads to a unique source of information about, e.g., environmental conditions and changes, activity patterns and health, and behavioral habits. By collecting this various data about the human body as well as its direct and extended environment, it is possible to create precise personal profiles including massive amounts of sensitive information. Using computational statistics and machine learning, this data can often even be used to make behavioral predictions about an individual. Thus, protecting this data from unauthorized access and unintended use during the whole data life-cycle, i.e., during its collection, transfer, processing, storage, potential release, or final deletion, is a major challenge.

Even anonymization of data often mentioned in this context cannot convincingly eliminate this risk. By linking anonymized data to other (public) data sources, it is often possible to infer identities. The likelihood of successful matching increases with the number of linkable parameters (Rocher et al. 2019). An example of such indirect leakage is location data. Tracking a person's location inevitably implies collecting and processing data about the whereabouts—and thus the behavior—of persons. This often allows to infer highly sensitive information about users' activities, like maybe sexual habits/orientation, drinking and social behavior, physical or mental health, religious and/or political beliefs. A famous example of the analysis of driving behavior is the 2012 Uber blogpost "Rides of Glory",[4] in which Uber showed how to spot candidates for one-night stands among its riders. While the risks from location-based attacks are fairly well understood given years of previous research, our understanding of the dangers of other modalities (e.g., activity inferences, social network data) are less developed.

For some data, the impact on an individual's privacy appears insignificant at first glance, but contains sensitive information that can be derived or inferred

[4] https://web.archive.org/web/20140828024924/https://www.blog.uber.com/ridesofglory.

from the data. Most users are not aware of the amount and extent of data as well as the expressiveness and significance of the collected data. Since Sweeney's work (Sweeney 2002) on de-anonymization through seemingly anonymized, innocent data, many other examples of de-anonymization attacks have been reported. This includes those of the web search queries of over half-million America Online (AOL) clients (Barbaro and Zeller 2006) and the movie reviews of a half-million Netflix subscribers (Narayanan and Shmatikov 2008).

In AOL's case, user IDs of search queries were replaced with unique identifiers per user to allow researchers using the data to access the complete list of a person's search queries. Unfortunately, the complete lists of search queries were so thorough that individuals could be de-anonymized simply based on the contents of search queries. In the Netflix case, Narayanan and Shmatikov used a different approach and re-identified several Netflix users by correlating the available research data with publicly available movie ratings data. In addition, they were able to infer more sensitive information from the available data since "[m]ovie and rating data contains information of a more highly personal and sensitive nature. The member's movie data exposes a Netflix member's personal interest and/or struggles with various highly personal issues, including sexuality, mental illness, recovery from alcoholism, and victimization from incest, physical abuse, domestic violence, adultery, and rape."[5]

These examples have shown that the concept of personally identifiable information (PII) is a challenging concept that is not as straight-forward as it appears. Due to the diversity and efficiency of modern de-anonymization algorithms (Narayanan and Shmatikov 2008, 2009; Rocher et al. 2019), it is often possible to re-identify an individual, even in the absence of immediate personally identifiable information. While some attributes in personal data may not be identifying uniquely on their own, almost all information can be personal or identifiable when combined with enough other relevant context information (Narayanan and Shmatikov 2010).

Furthermore, an intentional sharing or unintended leak of personal data brings new challenges, since a data set cannot be protected to preserve privacy once it becomes public. A major challenge is thus to determine whether the data stored or to be released is sufficiently and adequately anonymized not only for today's de-anonyzation techniques but also for future ones yet to be developed. There is a growing number of examples and techniques for reconstruction attacks, where data that may look safe and innocuous to an individual user may allow sensitive information to be reverse-engineered. This also means that your data may have to be regularly reconsidered for their privacy sensitivity.

Starting from a background of legal and ethical obligations to safeguard privacy, we have illustrated how difficult and complex the notion of anonymization and privacy protection is. It becomes evident how privacy and data protection need to become essential elements in mobile sensing. Motivated by data protection regulation such as the GDPR, one needs to actively consider how to limit the collection, flow, use/processing, storage, release, and deletion of personal data in own research. This is in contradiction to the researcher's desire to share its primary data to enable

[5] http://www.wired.com/threatlevel/2009/12/netflix-privacy-lawsuit.

reproducibility of results or to facilitate follow-up research. We will next illustrate what role Privacy Enhancing Technologies (PETs) can play in this protection and how they can be embedded in a privacy engineering process to design mobile sensing systems that even could enable Open Science principles.

2.4 Privacy Protection

We will start our discussion on how to technically protect privacy in mobile sensing with a recap of some GDPR principles as listed in Article 5. It already foresees legitimate purposes related to scientific research and statistics, for which specific rules are outlined in Article 89. There is also an exemption that states personal data may be archived for these purposes (which would normally violate the storage limitation principle). However, these processing and archiving of personal data for scientific research is subject to the condition that technical *and* organizational measures (TOMs) are taken to protect the data. As discussed earlier, Article 25 of the GDPR specifies that data protection should be implemented by design and by default but it leaves open what this could mean in practice. In this section, we now discuss examples how one can practically implement this requirement.

Hoepman (2014) introduced a set of *strategies* to improve privacy during the design process of an IT system. They provide overarching categories to then derive more specific design patterns that can be used to finally select appropriate technical and organizational measures to protect personal data. Hoepman's strategies are called *Minimize*, *Separate*, *Aggregate*, *Hide*, *Inform*, *Control*, *Enforce*, and *Demonstrate*. Taking *Aggregate* as an example, this strategy states that "Personal data should be processed at the highest level of aggregation and with the least possible detail in which it is (still) useful". For publication and archiving of scientific data, this strategy is often used when dealing with particularly sensitive information, such as personal profiling or health-related data. On the technical side, privacy design strategies are used to classify privacy patterns, the goal of which is to provide proven best practices for some settings and enable "off-the-shelf" usage of PETs. As discussed by Hoepman (2014) and others, not all strategies have received sufficient attention from research, and the technological maturity varies greatly between PETs. However, recent years have seen significant improvements in this regard and we highly recommend the use of these strategies and review of available privacy patterns and PETs when considering processing of personal data, especially in the context of mobile sensing or big data.

Returning to the fitness tracker example from the introduction, we now describe the practical application of the *Aggregate* strategy. For the purpose of monitoring fitness activity and overall health, a fitness tracker collects information such as the average heart rate, as well as the minimum and maximum rates during a sport session. Rather than collecting each pulse measurement and sending it directly to a server where it is stored, the aggregate strategy recommends local aggregation of this information in a way that is consistent with application goals. For example, to monitor overall health and track fitness, the average, maximum and minimum heart rates over the past minute can be computed in the device and transmitted. This information reveals a lot less about activities compared to per-second measurements. In this specific example, note how the aggregate strategy has benefits beyond privacy; removing unnecessary data from the collection process reduces the bandwidth, storage, and processing time required to analyze the data, illustrating that privacy protection and data processing are not always a zero-sum game. Similar aggregation can be performed by discretization of continuous data (e.g., only collecting heart rate only as low, medium, and high heart); however, the information loss associated with this process may not be suitable for every application. For this reason, the choice of PETs is inherently dependent on what the data is used for; this is one reason why the GDPR requires a specification of purpose for data processing and entails that domain experts and privacy experts need to work hand in hand in such projects.

Another relevant example is the use of analysis techniques from “big data”. The purpose of these techniques is to extract useful patterns from large volumes of data. In such settings, the volume of data is too large to be analyzed on a regular computer, and thus computations are performed on the data by a distributed database or a compute cluster. In medical and psychological applications, the interesting patterns are typically correlations between observable behaviors and markers on the one hand and associated conditions on the other. These can be computed by the database directly, therefore removing the need for direct access to the data, although this access is often still available. Cryptographic research has dedicated significant effort (Lindell and Pinkas 2002) to the design of *privacy-preserving data mining* techniques, whose goal is to extract such patterns reliably, while being able to provably *hide* the individual inputs and thus protect them from misuse. This privacy design strategy particularly suitable for situations where aggregation or minimization are difficult to apply. In those situations, privacy-preserving data mining techniques offer a compromise between privacy and data access: a researcher can run certain analyses on encrypted data, but not retrieve an individual’s data from the data set. For example, using suitable protocols like Secure Multi-Party Computation or Secure Function Evaluation, it is possible to calculate certain averages on data while keeping the individual data items savely on the devices of the data owners. However, this often requires to carefully think about the analysis one wants to conduct before collection of data, since the modes of analysis are necessarily restricted in order to preserve privacy. Here, careful compromises between privacy and possible use of the data need to be found. Another approach would be to enclose data and its processing in secure “containers” inside computing systems where it cannot be easily be exfiltrated from. Intel’s SGX technology is an example for such a secure enclave technology available in many of today’s CPUs. Examples of such solutions that limit data access to policy-compliant operations were shown, for example, by Kargl et al. (2010), Al-Momani et al. (2018), or Meißner et al. (2021). Those solutions may allow more flexible analysis but provide different and maybe weaker privacy guarantees. Another aspect to consider is the technological maturity of these approaches as research prototypes and—in some cases—substantial computation or communication overhead.

2.5 Conclusion and Outlook

With this chapter we aimed to raise the awareness of privacy in mobile sensing. We outlined how legal and ethical considerations require every researcher applying mobile sensing to carefully consider the privacy implications of such data collection, and to apply a privacy by design and default process to come up with the best protection possible while still keeping the data useful for the researchers.

Current legal frameworks for privacy and data protection clearly state that collecting a consent form from study participants is not sufficient in most cases. Additional technical and organizational measures should be put in place to increase privacy protection. This typically involves collaboration with privacy experts with appropriate legal and technical background. As privacy is an inherently interdisciplinary topic, privacy researchers are always eager to find interesting, challenging use cases and data to which their technologies may be applied. The appropriate and visible application of such technologies can lead to an increase in user trust, while also reducing the impacts of specific biases, such as social desirability bias.

While not all technologies are readily available, the field is evolving rapidly, and there is an increasing interest in the research community to apply these new technologies in challenging applications, including mobile sensing, digital phenotyping, and psychoinformatics. It is important that privacy becomes a core value embedded into its foundations. Joint research and progress in this field is important also in order to close the gap between the desires for open science on the one hand and strong privacy requirements and responsible research on the other.

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Chapter 3
Ethical Considerations of Digital Phenotyping from the Perspective of a Healthcare Practitioner Including Updates

Paul Dagum and Christian Montag

Abstract In this chapter we introduce digital phenotyping and its applications to healthcare. Despite the promise of this new form of clinical diagnosis in medicine and psychiatry, use of digital phenotyping raises several ethical concerns. We use insights derived from a clinical case study to frame these different ethical questions. We discuss how current healthcare practice and privacy policies address these questions and impose requirements for non-healthcare scientists and practitioners using digital phenotyping. We emphasize that this chapter frames the discussion from the perspective of the healthcare practitioner. We conclude by briefly reviewing more strongly theoretically based discussions of this emerging topic.

3.1 Digital Phenotyping

The term *digital phenotyping* was first introduced in 2015 by Jain et al. (2015) as a modern-day adaptation of evolutionary biologist Richard Dawkins' 1982 concept "extended phenotype". Dawkins argued that phenotypes should not be limited to observable characteristics of biological processes but should be extended to include all observable characteristics including behavior. A digital phenotype was conceptualized as an extended phenotype that used online activity and behavior data that could be linked to clinical data to improve diagnosis and prognosis. While the original concept of digital phenotyping was largely behavioral motivated, prior research on clinical measurements from wearable sensors (Elenko et al. 2015) to cognitive function and mood (Dagum 2018; Kerchner et al. 2015; Messner et al. 2019) embraced this nomenclature. A more recent discussion of digital phenotyping by Torous et al. (2017) extends the concept to include digital self-reports and physiological measures

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_3

from sensors. Insel (2017) positions digital phenotyping in a clinical context of measurement-based care enabled by digital measures of behavior, cognition and mood.

Digital phenotyping broadly encompasses two distinct areas: *behavioral phenotyping* and *digital biomarkers*. Behavioral phenotyping more closely resembles the original definition of digital phenotyping. Behavioral phenotyping is the use of digital information such as location tracking, motion sensors and email, text or call activity to infer behavior-expressed symptoms (Chittaranjan et al. 2013; Montag et al. 2014, 2019). For example, symptoms of anhedonia may manifest as a decrease in locations visited or email and text activity (Jacobson et al. 2019; Markowetz et al. 2014; Saeb et al. 2015). Behavioral phenotyping also encompasses the use of social media "likes", post content or search terms to infer changes in behavior, mood and personality (Kosinski et al. 2015; Marengo and Montag 2020; Marengo et al. 2021).

Digital biomarkers purport to measure trait and state changes in neuropathology that can be indicative of disease risk, disease onset, disease progression or recovery. The Biomarkers Definitions Working Group defines a biomarker as "a characteristic that is objectively measured and evaluated as an indicator of normal biological processes, pathogenic processes, or pharmacological responses to a therapeutic intervention" (Biomarkers Definitions Working Group 2001). HbA1c is an example of a serum-measurable biomarker used to manage diabetes. Another example of a biomarker is the interval between the onset of the Q wave and the conclusion of the T wave in the heart's electrical cycle, known as the QT interval. There is an association with QT interval prolongation and fatal cardiac arrhythmias, making QT a widely used safety biomarker in drug development.

Digital biomarkers are examples of biomarkers extracted from the data created by the use of digital devices such as smartphones and wearable devices. Despite considerable recent interest in this field there are no examples today of a digital biomarker that would fully satisfy the Biomarkers Definitions Working Group criteria. Possibly one example is the early work that validated digital biomarkers of cognitive function against gold-standard psychometric instruments (Dagum 2018). While these early results are promising, further work is needed in this exciting area. In this context, we also hint towards the discussion around the blurred boundaries in correctly defining a digital biomarker (Montag et al. 2021a). At best digital biomarkers should consist of digital footprints providing *direct* insights into human (neuro-)biology. In so far the put forward example from Dagum (2018) would rather represent an *indirect* digital biomarker, because the assessed cognitive functions arise from the brain. For more on the digital biomarker definition issues see a recent paper by Montag et al. (2021a) and also Chap. 31 in this book. For an overview on recent studies touching upon more direct digital biomarkers see Montag et al. (2021b).

3.2 Digital Phenotyping in Healthcare

In healthcare delivery, digital biomarkers are emerging as a clinical measure used by care providers for clinical decision making. Mindstrong Health Services, a California based healthcare provider for individuals with a serious mental illness uses an application running on a member's smartphone to create digital biomarkers and to provision telehealth services (mindstronghealth.com).

To make ethical considerations of digital phenotyping concrete, we describe how Mindstrong's digital biomarker application and healthcare services are used in crisis prevention. The continuum of crisis services is a cycle of prevention, intervention, response and stabilization. Unfortunately, patients with serious mental illness experience primarily respond-and-stabilize services. The goal of crisis services should be to preempt and intervene before a crisis occurs. In the early period of clinical decompensation low acuity interventions delivered through telehealth can be sufficient. The challenge in achieving this goal has been the lack of valid, objective and ecological measures of worsening function to alert the provider. Digital biomarkers have the potential to detect clinical deterioration experienced early but not reported by the patient.

3.2.1 Case Report: Patient AB[1]

We consider the following case report of patient AB in her 40s with a history of bipolar disorder and psychosis. AB was enrolled in the Mindstrong Health service. Enrollment involved downloading the Health by Mindstrong application (app) on her smartphone. The app captures the data needed to create five digital biomarkers (here meant as rather indirect digital biomarkers). The biomarkers are computed daily from the AB's normal use of her smartphone by measuring response times to different patterns of tapping and swiping that she used repeatedly throughout the day. These biomarkers are *transdiagnostic* meaning that they are not specific to any particular diagnosis. Each biomarker measures state-dependent changes in cognition or mood that may be indicative of illness relapse.

Figure 3.1 illustrates the digital biomarker data available to AB in the Mindstrong app on her smartphone. Shown in the figure is the biomarker for cognitive control over several days, with each "dot" representing a day. On a smartphone, cognitive control can be measured from a subject's tap reaction times and the variability in reaction times to certain events that are aggregated throughout the day during the subject's normal phone use. During this period AB's daily cognitive control is within the white zone set at ± 1.5 standard deviations. The light pink zone covers ± 2 standard deviations and values outside that range will alert both AB and the clinician. Figure 3.1 shows a period of good cognitive control whereas Fig. 3.2 shows a period

[1] We obtained the patient's informed consent to publish this material. The patient's initials were changed to protect her privacy.

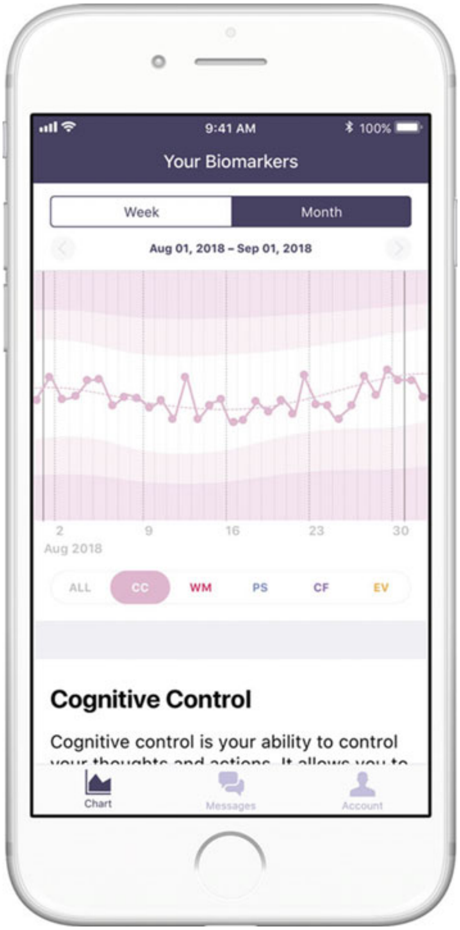

Fig. 3.1 Shown is AB's cognitive control (CC) digital biomarker in August 2018. Each filled circle corresponds to a daily measurement. The white zone spans ±1.5 standard deviations and the light pink zone spans ±2 standard deviations. During August we note that AB's cognitive control remained in the white zone

of erratic swings in cognitive control outside of the ±2 standard deviation zone. Note the break in data between September 20th and September 25th. With the Mindstrong app on her smartphone, AB has 24/7 access to Mindstrong Health Services licensed providers via secure messaging and private videoconferencing. Figure 3.3 shows messages exchanged during the period of erratic variability just before the break in the data. When the digital biomarkers are outside the ±2 standard deviation zone, AB and her Mindstrong Health Services care manager receive alerts. Figure 3.4 shows an expanded view of the cognitive control biomarker and working memory biomarker during the period of erratic variability. During the four-day break in the data, AB was hospitalized and treated for relapse. Post-discharge from the hospital we notice significant improvement in ABs digital biomarkers. Immediately following discharge AB communicated to her Mindstrong Health Services care manager the following:

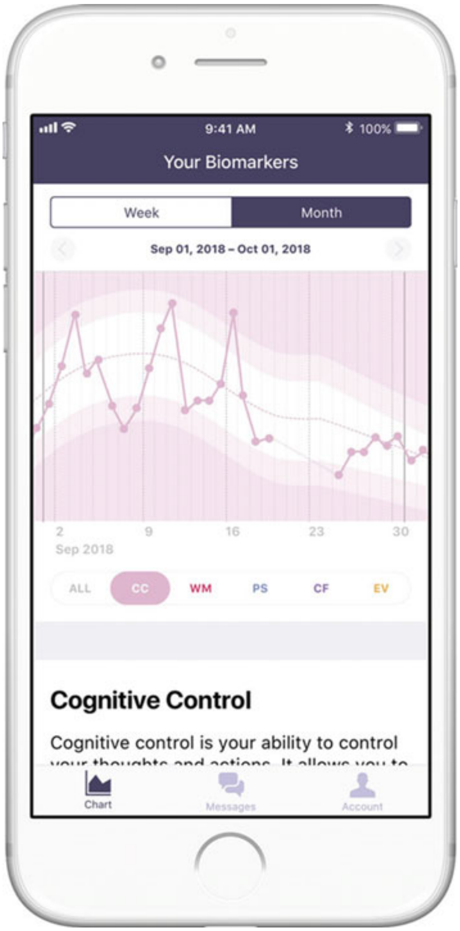

Fig. 3.2 Shown is AB's cognitive control biomarker in September 2018. During this period, we note erratic variability in her biomarker with swings into the light pink and dark pink zones that exceed ±2 standard deviations. We also see a break in the data beginning September 20 and ending September 24 when she was hospitalized

> I'm doing a lot better. I was experiencing a lot of auditory hallucinations. They made it difficult to sleep which made things progressively worse.
>
> I checked myself into the hospital. They adjusted my medications, gave group therapy, and monitored me. I believe I slept for 12 hours each night 3 days in a row. What a relief! The hallucinations finally subsided.

AB's transparency following her hospital admission about her symptom burden and clinical decline was markedly distinct from pre-hospitalization. Agency is a recurring theme in mental health. AB's need to stay in control of her illness was evident in retrospect. Safety is the other recurring theme in mental health and represents an individual's desire to be alerted to impeding risks in their condition early while they still have agency.

Figure 3.5 illustrates the user and provider journey through crisis prevention beginning with increased symptom burden and functional decompensation detected by

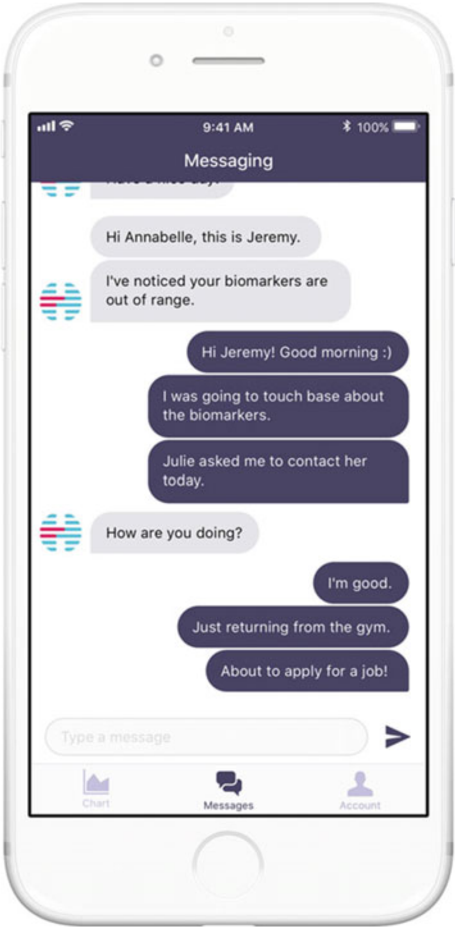

Fig. 3.3 Shown is AB's communication with her Mindstrong Health Services care manager prior to her hospitalization. AB had 24/7 access to her Mindstrong care manager and both her and the care manager received automated alerts when AB's biomarkers were outside of the ±2 standard deviation zone. The names of AB and her Mindstrong care managers were changed to protect privacy

changes in digital biomarkers captured from the user's smartphone. A care manager or other care professional contacts the user through secure messaging or videoconferencing to clinically evaluate the individual and confirm that the observed changes in digital biomarkers represent a clinical decompensation. On confirmation, the patient is escalated to a licensed clinical psychologist for evidence-based telehealth therapeutic interventions and re-evaluated regularly for improvement. If the patient does not improve or continues to decompensate, care is escalated to a telepsychiatric consultation or a clinic consultation.

AB's case report highlights a number of ethical areas that require consideration.

1. Does the informed consent properly explain the relevant risks and benefits to AB, the range of data collected, and the digital phenotype findings that are derivable from that data?

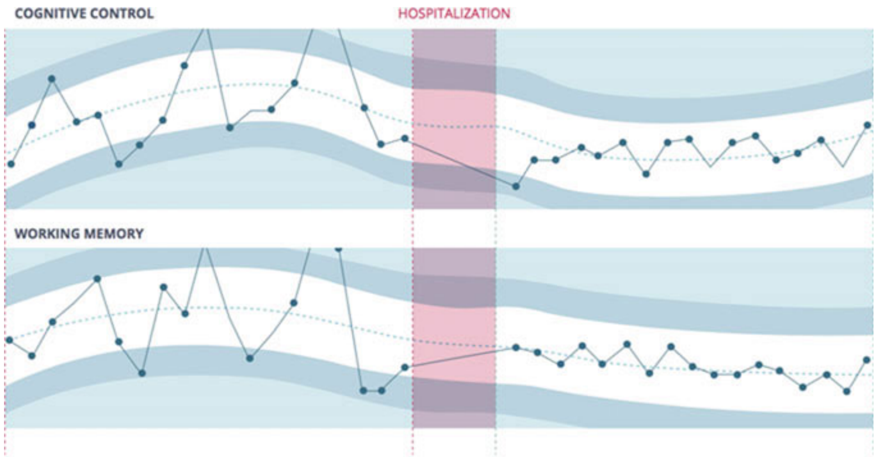

Fig. 3.4 Shown are AB's digital biomarkers for cognitive control and working memory pre-hospitalization and post-discharge. AB is successfully stabilized during her hospital stay. AB's cognitive control and working memory biomarkers return to their healthy baseline following discharge

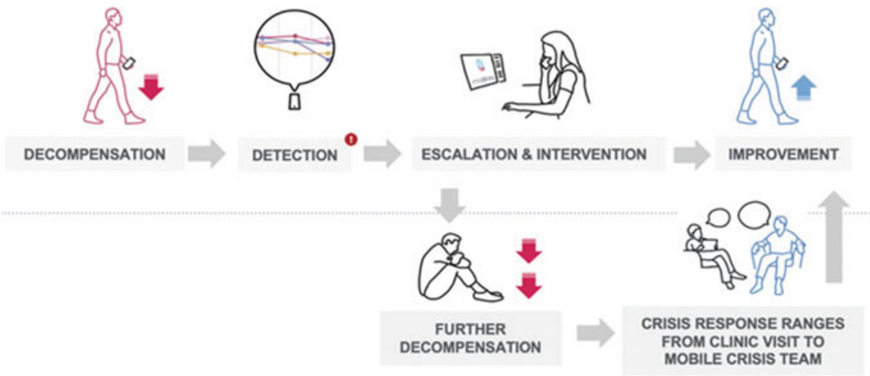

Fig. 3.5 An illustration of a user journey through decompensation, early intervention and crisis intervention while on the mindstrong health app and receiving mindstrong health services

2. Does the informed consent properly disclose who has access to her data and digital phenotyping findings that can be derived from her data?
3. Did AB consent to receive evidence-based telehealth care based on the digital phenotype findings?
4. Did AB and her provider understand the intended use of digital phenotyping?
5. Was AB informed about the security of her data and restrictions to its access?

3.2.2 Informed Consent

In healthcare, digital phenotyping can be viewed as a risk indicator of an adverse outcome and can inform clinical decision making. In the United States, informed consent that properly explains the relevant risks and benefits to the patient is necessary and sufficient to receive healthcare services. Like diagnostic tests that require tissue or blood samples from which multiple test can be run, the data samples required for digital phenotyping can also be analyzed differently to reveal new findings. It is worth noting that in European countries, under GDPR informed consent may not be sufficient (see Chap. 2 by Kargl et al.).

Digital phenotyping in healthcare qualifies as protected health information. State and federal regulations govern the conditions of access to protected health information (PHI). The Health Insurance Portability and Accountability Act (HIPAA) of 1996 in the United States provides data privacy and security provisions for safeguarding medical information. The HIPAA Privacy Rule allows HIPAA-covered entities, such as healthcare providers and health plans, to use and disclose individually identifiable PHI without an individual's consent for treatment. In all cases, sharing of individually identifiable PHI must be limited to the minimum necessary information to achieve the purpose for which the information is disclosed.

If protected health information needs to be disclosed for one of the following purposes, a HIPAA release form must be obtained from the patient:

- Disclosure of PHI to a third party for reasons other than the provision of treatment, payment or other standard healthcare operations. For example, disclosing data to an insurance underwriter
- Use of PHI for marketing or fund-raising purposes
- Disclosure of PHI to a research organization
- Disclosure of psychotherapy notes
- Sale or sharing of PHI for remuneration.

3.2.3 Intended Use

Clear language must accompany the intended use of digital phenotyping in healthcare. For example, the Mindstrong Health application is intended for adjunctive remote health management of patients under the care of a behavioral health provider for one or more serious mental illnesses, including schizophrenia, bipolar disorder, and major depressive disorder.

3.2.4 Security and Access

When working with PHI, a systematic approach to managing this information is necessary to ensure it remains secure. The approach which includes people, processes and IT systems, should be independently audited on a yearly basis. The International Organization of Standardization (ISO) and The Health Information Trust Alliance (HITRUST) are two certification organizations.

ISO is an independent, non-governmental international organization founded in 1946 and headquartered in Geneva. ISO has members from 164 countries and 786 technical committees and subcommittees involved in maintaining and improving standards developments (ISO—International Organization for Standardization 2019). The ISO 27000 family of standards certifies an organization's policies, procedures and controls for securing information assets. HITRUST is a private certification standard in the U.S. that like ISO 27001 certifies organizations on their security framework for the creation, access, storage or exchange of sensitive information. ISO 27001 or HITRUST certification is often required before sharing sensitive information such as PHI between organizations.

The ethical areas discussed here overlap with the work of Fuller et al. (2017) that focuses on medical research. The authors reflect on ethical implications in the context of location and accelerometer measurement and point to four areas of relevance, namely consent, privacy and security, mitigating risk, and consideration of vulnerable populations (page 87). In Table 1 on page 87 of their work they summarize their position that consent should be renewed during the clinical study after participants are provided their actual collected data. We also hint towards a new work reflecting upon how to increase benefits and reduce harm in the area of digital phenotyping (Montag et al. 2020).

3.3 Digital Phenotyping in Medical Research and Drug Discovery

New clinical tests and measurements create new opportunities for discovery in medicine. Digital phenotyping is not an exception. Pharmaceutical companies have been among the first to embrace the potential of digital biomarkers (Dorsey et al. 2017; Madrid et al. 2017; Rodarte 2017; Smith et al. 2018). Patient stratification using daily, ecological, multidimensional measures of cognition and mood may be indicative of who will respond to a new drug or intervention. Digital phenotyping can provide new digital endpoints to clinical trials that are proximal to patient function, improving on existing symptom reported outcomes.

Medical research on human subjects needs to be reviewed and approved by an independent ethics committee known as an institutional review board (IRB). The purpose of the IRB is to ensure that the rights and welfare of humans participating as subjects in a research study are protected. IRBs provide scientific, ethical, and regulatory oversight of human subject research. Part of the review is the informed consent process which must clearly explain to the individual the risk and benefits from the proposed research. Human subject research that involves digital phenotyping must follow these established guidelines.

More research is necessary to understand how participants perceive their anonymity in study designs using digital phenotyping and how it is explained in the informed consent. We need to consider new methods to ensure subject privacy, a topic that is further developed in the privacy Chap. 2 of this book by Kargl et al. and in empirical work by Nebeker et al. (2016).

Fuller et al. (2017) ask if researchers need to protect subjects from imminent harm in a study. The authors discuss if GPS data of a study should be used to find a lost child. The authors take a stance that researchers should not be burdened by these requests and this also needs to be made clear in the consent form. In contrast, incidental findings on a brain scan in a study that is using for example functional magnetic resonance imaging would ethically need to be reviewed by a licensed radiologist and communicated to the subject. Other considerations include whether researchers should be obliged to report illegal activity detected in data patterns to law officials.

Finally, we need to consider vulnerable groups such as children who need stronger protection and vulnerable groups that may be systematically excluded because of limited access to the internet and mobile devices (Hokke et al. 2018). In this context, researchers recently discussed the importance of several prerequisites to be able to use the internet and mobile devices including technical, reading and writing competence (Rubeis and Steger 2019). Such skills need to be considered when designing mental health applications.

3.4 Uses of Digital Phenotyping Outside of Healthcare

Non-clinical uses of digital phenotyping are varied. Examples of non-clinical uses include government, employers, education, direct-to-consumer marketing and insurance risk stratification. Non-clinical use of health information that in a clinical context would be regulated, strains existing ethical governance rules. Government today performs DNA tests on prisoners willingly or under court mandate. The DNA test can be used as forensic evidence but can also provide other information about the subject. For neuropsychological testing of prisoners, ethical guidelines exist (Vanderhoff et al. 2011) and should be used for digital phenotyping. This is also more and more relevant because societies are moving towards a totally connected Internet of Things, where many psychologial variables will be able to be predicted without asking people to fill in inventories or do structured interviews (Montag et al. 2021c).

In the workforce, behavioral phenotyping from posts in social media sites can influence hiring decisions (CareerBuilder 2018). This practice is mostly used to screen-out applicants but on occasion can be helpful if an applicant has contributed a well-written post relevant to their career. The use of Facebook data to predict personality traits, voter preferences, mental states or suicide risk (Eichstaedt et al.

2018; Kristensen et al. 2017; Matz et al. 2017; Reardon 2017) represent other non-healthcare examples of behavioral phenotyping. The connection between a user's posts and their future behavior is nuanced and requires the use of advanced machine learning algorithms trained on vast amounts of data (Elhai and Montag 2020). In these cases, the user has less control or transparency of how their data and predictions of preferences and behavior are used.

Direct-to-consumer marketing has long exploited digital data to discover consumer preference to create an asymmetric commercial advantage. Both behavioral phenotyping and digital biomarkers have the potential to sharpen this asymmetric advantage against the consumer. Behavioral phenotyping in the form of emotional response through Facebook likes or facial expression captured from a smartphone camera are in use today to market to consumers (Kosinski 2021; Marengo et al. 2022; Settanni et al. 2018; Wang and Kosinski 2018). In all these cases users should explicitly opt-into the use of their digital data for digital phenotyping. Informed consent would need to disclose all possible health-related findings that would be derived from the data captured and how that information would be used. For example, ads for therapists or psychiatrists targeting a user who is deemed to be depressed would feel invasive to most people.

The preceding practices highlight several ethical questions that are reminiscent of a HIPAA release form for PHI data.

- Who owns the user data?
- Who owns what can be inferred from the user data?
- Who decides what can be done with the user data?
- Can the data be used for marketing?
- Can the data be disclosed to other organizations?
- Can the data be sold or shared?

In this context, it would seem that the aforementioned uses of digital phenotyping should require explicit informed consent.

Insurance companies have increasingly used personal data to set premiums. Personal attributes such as occupation, level of education or credit score can significantly impact home and auto insurance premiums (National Association of Insurance Commissioners 2012). This practice has come under closer scrutiny with legislators in some states striking back at the use of such criteria claiming they unfairly discriminate against those who lack a college degree or work in certain industries. Several states have banned the use of credit information to set premiums. New York state went further and banned insurance companies from using occupation and education related criteria to set rates (Scism 2017).

Insurance companies claim that using these factors improves rating accuracy and avoids cross-subsidization, or the charging of higher prices for one group to lower the price for others. Cross-subsidization results in good drivers paying for the behavior of bad drivers.

It is interesting to contemplate whether digital phenotyping could improve rating accuracy without unfairly discriminating based on social economic status. Digital biomarkers that measure cognitive control, or impulsivity, are likely good predictors of risk. Similarly, measures of processing speed or attention should be indicative of higher or lower accident risk. Age is a strong covariate of these cognitive measures, showing a declining performance with advancing age. Auto insurance premiums also show an increase with advancing age beyond the 6th decade (Cobb and Coughlin 1998), possibly reflecting a higher risk with declining cognitive function. But using a population measure such as age to adjust premiums is very different from using an individual clinical measure such as a person's cognitive control biomarker. Data from onboard diagnostics in a car can determine the driver's gender, another attribute used in setting premiums and recently banned in California (Leefeldt 2019; Stachl and Bühner 2015). The question is whether insurance companies can use health information to set premiums.

Following the 2010 passing of the Affordable Care Act (ACA) in the United States, healthcare insurance companies where barred from using pre-existing health condition to increase a person's premium. Similarly, the Americans with Disabilities Act (ADA) of 1990 made it illegal for insurance companies to charge an individual a higher rate because of a physical or mental disability. The ADA is a civil rights law that prohibits discrimination against individuals with disabilities in all areas of public life, including jobs, schools, transportation.

Both the ACA and ADA establish an ethical and legal framework that limits an insurance company's ability to adjust premiums based on a pre-existing health condition or disability. The ADA further extends that framework to employers and education. The ADA defines a person with a disability as someone who has a physical or mental impairment that substantially limits one or more major life activities. Could certain behavioral phenotypes qualify as a pre-existing condition or a disability? Could digital biomarkers of cognitive function qualify as a pre-existing condition or a disability? Today they do not, but if that were to change, uses of digital phenotyping outside of healthcare would be limited and regulated by existing laws.

3.5 The Future of Digital Phenotyping

For over a century we have failed to develop objective clinical measures of mental health or sensitive ecological markers of cognitive function. The brain is a complex organ and unlike other organs, normal physiology and pathology cannot be measured through blood tests or physiological markers. Nonetheless, the paper-and-pencil gold-standard neuropsychological tests have demonstrated that we can create sensitive indicators of neural circuit dysfunction from repeated simple timed challenges (but see some thoughts on the future of psychological self-report inventories in Montag et al. 2021c). Human-computer interfaces on digital devices present parallel repeated simple timed challenges. These repeated timed challenges create a time-series of measurements because they are repeated frequently throughout the day during normal digital device use. The timings of those events, and the many features that can be extracted from those timings, can be used to reproduce the gold-standard tests objectively and are representative of the user in their ecological environment.

Thus, one might argue that the adoption of ubiquitous human-computer interfaces was a prerequisite for the development of ecological and objective clinical measures of the brain.

Digital phenotyping emerged from the ubiquitous adoption of digital devices and explosion of online user data. This data is collected by the websites and telecommunication companies that provide service to the devices. Online data has been used to influence user behavior since 2000. Privacy policies emerged during this period, but they addressed direct marketing uses of the data. Beginning in 2013, early work at Mindstrong demonstrated that the HCI data from smartphones could be converted into validated clinical measures of cognitive function. Subsequent findings demonstrated that posts used in Facebook could be used to predict depression about three months before a formal diagnosis (Eichstaedt et al. 2018). The misuse of such information and data privacy sparked ethical concerns (Martinez-Martin et al. 2018).

Ethical considerations of digital phenotyping can proceed along two directions. We can choose to categorize digital phenotyping as protected health information. This approach is pragmatic and allows us to leverage an established and proven framework for individual consent, governance and control of the data. That has been the direction taken at Mindstrong. As future research continues to validate clinical use of digital biomarkers, considering digital phenotyping as protected health information is appropriate.

Alternatively, we can choose to construct a de novo regulatory framework for digital phenotyping. This path is appropriate for digital phenotypes that are not clinical measures or when health information will not be identified from the data. For example, certain behavioral phenotypes are expressions of preferences and may not qualify as health information. But a de novo regulatory framework may not be a pragmatic solution. Such a framework would need to anticipate all future possibilities and uses of the data.

Human-computer interfaces will continue to evolve from touch-screen interfaces to augmented reality to direct brain-computer interfaces. Throughout this evolution, the data available to create digital biomarkers and phenotypes will continue to improve as will prognosis and prediction of brain-related disorders. To safeguard a better future, we must collaborate with policy makers, regulatory bodies, insurance companies, healthcare systems and technology companies to agree on proper governance and use of this data.

Conflict of Interest Christian Montag mentions that he currently received funding from Mindstrong Health for a project digital phenotyping. Beyond that he serves as scientific advisor for Applied Cognition, Redwood City, CA, USA. This activity is financially compensated. Of importance, his views on ethics as presented in this work have not been influenced by this financial support for his research. Paul Dagum is the founder of Mindstrong Health, a company developing digital phenotyping products for mental healthcare delivery. He served as its Chief Executive Officer from its founding in 2013 through October 2019 and was granted five U.S. patents on digital phenotyping and digital biomarkers. PD is currently co-founder and CEO of Applied Cognition developing diagnostic and therapeutic solutions for Alzheimer's disease. PD owns stock in Mindstrong Health and in Applied Cognition.

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Part II
Applications in Psycho-Social Sciences

Chapter 4
Computerized Facial Emotion Expression Recognition

Mattis Geiger and Oliver Wilhelm

Abstract Facial emotion expressions are an important gateway for studying human emotions. For many decades, this research was limited to human ratings of arousal and valence of emotional expressions. Such ratings are very time-consuming and have limited objectivity due to rater biases. By exploiting improvements in machine learning, the demand for a swifter and more objective method to assess facial emotional expressions was met by a plethora of software. These novel approaches are based on theories of human perception and emotion and their algorithms are often trained with massive and almost-generalizable data bases. However, they still face limitations such as 2D recognition and cultural biases. Nevertheless, the accuracy of computerized emotion recognition software has surpassed human raters in many cases. Consequently, such software has become instrumental in psychological research and has delivered remarkable findings, e.g. on human emotional abilities and dynamic expressions. Furthermore, recent developments for mobile devices have introduced such software into daily life, allowing for the immediate and ambulatory assessment of facial emotion expression. These trends provide intriguing new opportunities for studying human emotions, such as photograph-based experience sampling, incidental or implicit data recording in interventions, and many more.

4.1 Introduction

From planning behavior, over automated decision-making, to actual behavior such as communication—emotions shape our everyday life. It comes as no surprise that emotions are among the most researched topics in psychology and related disciplines. When it comes to social interaction, the communicative function of emotions is of key interest. That is, emotions elicit automatic expression and influence controlled

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*,
Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_4

communication behavior. Typical emotion communication behavior includes vocal or facial expressions, such as crying or smiling. It serves as a fast and automatic pathway for the distribution of information into our social environment, e.g. about dangers or requests for help, and thereby facilitate survival (Darwin 1987). Throughout the history of emotion research, there has been a demand for the systematic assessment of emotion communication. Initially, this demand was met by having human raters go through records of emotional behavior. In the last decade, there has been a rise in the development and use of facial emotion expression recognition software.

In this chapter, we focus on facial emotion expression and its recognition by humans or machines. We will begin by introducing major theories of emotion expression and the tools developed to systematically assess facially expressed emotions with human raters. Next, we will describe contemporary approaches towards machine-based classifications of facially-expressed emotions, including machine learning. Limitations of current methods and perspectives to overcome them will be provided next. Furthermore, we present examples from basic and applied research to show how computerized emotion expression recognition software can facilitate and initiate research in fields that could not be tapped hitherto. We introduce the concept of socio-emotional abilities and present how emotion recognition software expands this field to emotion expression and emotion regulation abilities. Finally, we provide a number of examples to illustrate how mobile sensing of facially-expressed emotions can dramatically change research approaches towards emotion and how it can be useful in a variety of novel applied settings.

4.2 Human Facial Emotion Expression Recognition

Emotions are latent states and therefore not directly observable. In order to find proxies for these latent states, past research often focused on their physiological manifestations, such as heart rate or skin conductance. Although this research greatly improved our general understanding and theories of emotion, it is typically limited to the arousal dimension of emotions only. In general emotion theories (Cannon 1927; Schachter and Singer 1962; Scherer 2005), arousal refers to the general level of (physiological) activation due to an emotional state. Arousal is distinguished from the valence of emotions. In overarching emotion theories, valence is one dimension from positive to negative valence, whereas in theories of basic emotions valence dimensions are distinguished between emotions such as Anger, Happiness, Sadness, Surprise, Fear, and Disgust (Ekman 1992). In the latter system, emotional valence is categorized as six basic emotions that are universally recognized and that differ in evolutionary function. The communicative aspect of emotions provides the opportunity to differentiate both emotional arousal and valence and is therefore a vital pathway for the scientific study of emotions. Competing contemporary emotion theories disagree with the basic emotions approach of Ekman (1992). However, the vast majority of computerized facial emotion expression recognition tools are based on the basic emotions theory (Corneanu et al. 2016). Therefore, this chapter is restricted to basic emotion theory. We discuss limitations emerging from this restriction in the conclusion of this chapter.

Research on the communicative function of emotion requires a system to measure the nature and intensity of emotional communication signals. The most popular systematic approach in this domain is the Facial Action Coding System (FACS; Ekman and Friesen 1978). In the FACS, distinct facial movements, such as moving the corner of the lips upwards, for example as part of a facial expression evaluated as a smile, are categorized as Action Units (AUs). Furthermore, AUs are anatomically valid: for every AU, a single muscle or a group of facial muscles that initiate AU-movement is/are identified. For example, when frowning, which is coded as AU4, the musculus corrugator is active. FACS raters use these AUs to evaluate facial expressions of persons. Typically, raters are presented with a picture and rate the displayed expression for every AU on a 5pt-Likert scale. Basic emotions are characterized by a distinct pattern of activated AUs (Ekman 1992). These patterns are listed in the FACS Affect Interpretation Database (FACSAID; Ekman et al. 1998). For example, a happy expression consists of AU6 (cheek raiser) and AU12 (lip corner pull). If, among all AUs, only these were rated as active, then the FACS rater would conclude that the facial expression is happiness.

Although the FACS greatly advanced research on facial emotion expressions, much research in this field still relies on self-reports from participants experiencing or expressing the emotion. The main reason for this is probably that gathering FACS ratings is extremely effortful, time-consuming, and costly—to the point where conducting research with large samples of participants and/or many time-points becomes unfeasible. The predominant use of human raters also leads to a neglect of the dynamic nature of facially-expressed emotions. Clearly, videos should be preferred over pictures (Tcherkassof et al. 2007), but having raters evaluate each frame from a lengthy video is usually unrealistic due to the resources required to do so. In addition, due to common biases in human raters, multiple raters are required for achieving reliable and objective ratings, which multiplies the required rating effort. Consequently, less effortful, more objective, much quicker, and cheaper procedures for rating facial emotion expressions are essential for advancing research and applications in this field.

4.3 Computerized Face Perception

The evaluation of facial emotion expressions might meet the requirements of effort, prize, speed, and objectivity if accomplished through machines. Typically, this evaluation is ‘taught’ to computers akin to how these skills function in humans. In one widely acknowledged approach, Bruce and Young (1986) distinguish two very basic levels of information codes in face recognition that also apply to the functionality of face detection in computers: pictorial and structural code. Pictorial code refers to any information that constitutes a picture. For a digital file, that would be the pixels and related information, such as the color or brightness of every pixel in a picture.

Pictorial code is specific to an individual picture and not to an individual identity. Structural code refers to more abstract information that is derived from the pictorial code, such as the black circle shape of the pupil, which might appear in varying positions in different pictures, but still represent the same structure. In other words, structural code is about the invariant features of a face and it is built upon internal features of a face. For complete face detection, several structural codes are important, for example the eyes, the jawline, the lips, etc.

To detect structural code via software, texture analysis, such as Gabor filters, is used. This method mimics human visual perception via photoreceptor cells (Marĉelja 1980): it detects regularities (lines, curves, circles, complex shapes, etc.) in images by analyzing luminosity and color of pixels. Faces consist of many facial features that are combinations of such regularities. For example, the eyes consist of an outer roughly oval-shaped (as seen in neutral, frontal photographs of faces with open eyes) white structure (i.e. visible parts of the eyeball) and two inner circle shaped structures (i.e. the colored iris and the black pupil). Texture analysis tools—just like humans—are trained on large datasets to detect such structures and to thus separate structural code from pictorial code. Finally, humans and software classify the configuration of structural codes; for example, an eyeball, iris, and pupil "create" an eye, while two eyes, a nose, and a mouth "create" a face. This information is essential and indispensable to derive decisions about whether a picture is showing a (part of a) face or not. Furthermore, the organization of the structural code is essential for setting facial landmarks. Such landmarks are important for the analysis of changeable aspects of faces, for example when known identities express different emotions.

There is large variability in available algorithms for face detection (Zhang and Zhang 2010). Modern algorithms achieve high detection rates even in low quality recordings, such as with extreme lighting conditions or low resolutions. However, face detection algorithms are still developing. One common problem is that detection rates decrease when faces are not presented frontally. The cause for this deficit is 2D-based detection in such algorithms. Without the depth dimension, landmark position estimates are biased and therefore differ systematically from the real position in three-dimensional space. Consequently, recent developments focus on three dimensional face models generated from 2D video recordings (e.g. Jeni et al. 2015). This is a very important step to further approach human face detection abilities. However, real 3D recordings or 3D estimations from videos with sufficient information to estimate a 3D model are still rare (Zinkernagel et al. 2018). This is mostly due to the facts that (a) the possibility to do 3D recordings is still uncommon in regular commercial devices, such as smartphones, and (b) the computational power of common devices does not yet allow for real time 3D model estimation from 2D videos. Nevertheless, the field of computerized face detection is highly advanced and available tools continue to improve. The sophistication of contemporary face detection tools provides a strong basis for computerized facial emotion recognition.

4.4 Computerized Facial Emotion Recognition

Employing facial landmark detection established by face detection algorithms in the last decade provided the basis for the development of several proprietary and open-source tools for computerized facial emotion recognition (e.g. Affectiva Affdex, Affectiva 2018; OpenFace, Baltrusaitis et al. 2016; IntraFace, De la Torre et al. 2015; Facet, Emotient 2016b; FaceReader, Noldus Information Technology 2018; just to name a few). Although details of the algorithms are usually proprietary in commercial software, the general functionality is similar across tools. The steps required for this are outlined below and summarized in Table 4.1.

First, a face is detected from a picture and facial landmarks are located and set. In the next step, emotional expressions are recognized by comparing landmark positions relative to a neutral or unexpressive standard face. In available software, all these steps happen in 2D space. The choice of the standard face is crucial for the precision of

Table 4.1 Summary of typical steps and descriptions in computerized facial emotion expression recognition

Step #	Step name	Description
1	Data input	Data type (two- or three-dimensional) determines whether the following steps are conducted in 2D or 3D. Most current data are 2D, but with additional data (sufficient head movement and true physical length of landmark distances) 3D data can be inferred from 2D input
2	Face detection	Employing texture analysis (e.g. Gabor filter) structural code of faces is identified. If sufficient structural code to form a full face is identified, the face area is marked with a square (in 2D) or cube (3D). Subsequent steps only focus on the marked face area
3	Landmark detection	Facial landmarks (e.g. mouth corners, eye lids, eye brows, etc.) are identified and marked within the face area via texture analysis
4	Landmark movement/AU evaluation	Facial landmark positions relative to the face area are compared to a standard face or the previous image to estimate landmark movement/AU activity
5	Emotion evaluation	The combination of all landmark movement/AU activity scores is compared to prototypical emotional expressions and based on their overlap expression likelihood or intensity are evaluated. For example, if AU1, AU2, AU5, and AU26 are strongly active and all others are not, an expression is rated as a strongly surprised expression

the landmark movement estimation. Usually, this standard face is derived from large datasets of faces on which algorithms were trained via machine learning or similar methods (Corneanu et al. 2016). Reference to this standard face can be problematic, because it ignores individual differences in facial morphology and plasticity. For example, morphology can introduce a bias if a person has considerably broader lips than the standard face. Then, the landmark movement algorithm would score a movement of the lip corner landmarks even if the person shows a completely neutral expression. In other words, the neutral or baseline point (0) of landmark movement varies across persons and can therefore be biased to an unknown degree if a standard face is employed.

The intensity of a landmark movement (or AU) was also evaluated in comparison to a large dataset with maximally strong movement of the respective landmark. Again, machine learning is typically employed to retrieve the necessary parameters (Corneanu et al. 2016). However, similar to the individual baseline, the individual facial plasticity determines the maximal point of landmark movement. Consider for example the fact that, for reasons of individual differences in facial anatomy some individuals can maximally pull their lip corners wider than others. Persons with lower than average plasticity cannot reach the maximal landmark movement scores, even if the individual maximum movement is reached. Consequently, we recommend using an individual baseline and controlling for face plasticity if landmark movement is evaluated. This requires a short calibration, i.e. recordings of neutral faces and of maximal activation of a series of AUs.

For many applied and scientific purposes, it is important to provide a score that also expresses the intensity of an emotion expression. This scoring is usually based on landmark movements (or AUs) and scores are usually better if the full pattern of all landmark positions is considered. If the landmark movement pattern of an evaluated face closely resembles the typical pattern of an emotional face, which is derived based on large datasets of persons showing this expression, then the evaluated face receives a high score on the respective emotion. Importantly, the full pattern of all landmark movements should be evaluated and not only those that are part of the emotion evaluated. Consider, for example, the emotions surprise and fear. Following FACSAID, the AUs active in surprise (AU1, AU2, AU5 and AU26) are a complete subset of the AUs active in fear (AU1, AU2, AU4, AU5, AU7, AU20 and AU26). If only AUs active in surprise expressions were used for evaluation, then a maximal fear expression would always result in a maximal surprise score, too. Therefore, the evaluation of surprise expression needs to also consider inactive AUs, i.e. a high score is achieved if (among others) AU4, AU7, and AU20 are inactive. For a detailed depiction, see Fig. 4.1. Similar scenarios apply between the facial expression of states such as pain and orgasm (Chen et al. 2018).

Most programs offer scores for (a subset) of Ekman's (1992) basic emotions and the emotion contempt. Additionally, many programs also deliver AU scores or landmark movement scores which indicate AU activity. These data provide the opportunity to generate alternative emotion scores or develop scores for other expressions. For example, just as when experiencing strong emotion, experiencing strong pain automatically elicits specific facial expressions (Werner et al. 2017). Research on

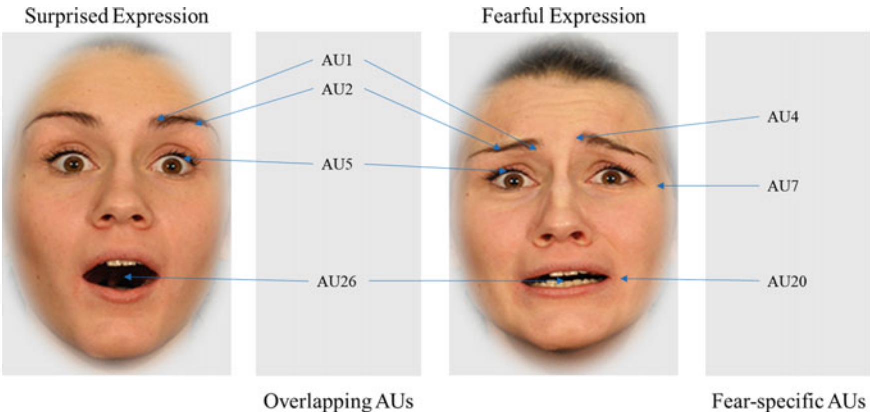

Fig. 4.1 An example of the Action Unit (AU) overlap of fearful and surprised expression, as described in the FACSAID (Ekman et al. 1998). AU1: inner brow raiser, AU2: outer brow raiser; AU4: brow lowerer; AU5: upper lid raiser; AU7: lid tightener; AU20: lip stretcher; AU26: jaw drop

pain expressions converges to a universal facial pain expression (Williams 2002; see also Chen et al. 2018), just like the universal emotion expressions of basic emotions. With this information, facial emotion expression recognition software that reports AU scores could also be used to score how much pain somebody experiences, for example in hospitals.

4.5 Limitations

Currently available software is not without limitations. The quality of decisions derived from programs that are based on machine learning methods (i.e. the precision of classification) hinges upon the validity of the underlying theory and employed training datasets (Zinkernagel et al. 2018). Obviously, the underlying theory, such as the comprehensive theory of basic emotions might be wrong or over simplistic. For example, the universality of basic emotions has been challenged by cultural differences in perceiving fear and disgust between Western and Eastern cultures (Jack et al. 2009). Other theories categorize emotions in largely different valence types (Scherer 2005). Assuming the facial expressions of fear and disgust were not universal, we would require culturally- or individually-adaptive software that judges an expression based on the cultural or individual background of a person. Such an endeavor is much more challenging than assuming that basic emotions are real, that they exist in every person, and that they have six prototypic manifestations representing distinct configurations of AUs—but this challenge is clearly an exciting new opportunity. In order to partly address this challenge, some developers began to train their algorithms on very diverse datasets, including a vast variety of ethnicities and achieved high performance for all of them (e.g. Emotient 2016b).

Yet, the software might still be biased because, so far, such software has usually been trained via supervised learning. In contrast to unsupervised learning, presuppositions about certain aspects of the training data are made during the training step during supervised learning (Hinton et al. 1999). For example, all pictures in a training dataset are pre-categorized according to western human FACS ratings in terms of the displayed basic emotion. If, however, there were culturally- or individually-different patterns of emotion expressions (as reported by Jack et al. 2009), such presuppositions would be wrong. Consequently, the software would have only learned the western configuration and would misjudge humans with the eastern configuration to express fear and disgust. Unsupervised machine learning might be deemed a solution for this problem. However, to be unbiased, this approach requires a facial expression training database that is perfectly representative of the whole world's population and would need constant training to account for changes over time, i.e. evolutionary conditioned changes in behavior. Acquiring such a dataset is currently inconceivable and consequently any software trained unsupervised would carry the sample bias of its training dataset.

Therefore, development and application of facial emotion expression recognition software must be cautious with respect to the cultural and individual background of their sample of training pictures and must consider measures such as improvement of data-basis, score adjustment, and constant training. In our example of eastern fear and disgust configuration, it might be sufficient to develop an alternative score. Jack et al. (2009) report a focus on the eye and nose region for eastern participants and a more holistic perception for western participants. Employing AU scores, it might be sufficient to only consider eye and nose AUs for eastern participants (e.g. fear AUs 1, 2, 4, 5 and 7) and all respective AUs (or the original fear emotion score) for western participants.

Another important limitation is that for proprietary software, relevant functional details are hidden in a black box. For proprietary products, it is usually not reported which databases are used to train the machine learning algorithms, how the databases are validated, and which machine learning algorithms were used for the different steps. Yet, for a sound assessment of such products information concerning the nature and use of the data bank are essential. For example: does it make a difference whether expressions stem from actual emotional states or were faked? Are the machine learning algorithms, such as support vector machines, neural networks and random forests relevant concerning categorization? This and further technical information are important for assessing the quality of a program and additional data are required to assess further aspects of classification accuracy.

Software developers report classification accuracy rates and often enough conclude that the software is valid and reliable (e.g. Emotient 2016a, c). Furthermore, results indicating that the software is not prone to systematic biases (such as lighting conditions) and recommendations for configuration (such as settings for video recording) are provided. However, evaluations independent of the software developers are required, too. Recent evaluations provide promising results. For example, scores of computerized facial emotion recognition software are equally precise or more precise than untrained human raters (Krumhuber et al. 2019, 2021) and such scores provide reliable estimates of emotional intensity in dynamic expressions (Calvo et al. 2018). Software scores correlate strongly with corresponding intensities from electromyography measurement (Kulke et al. 2018). Yet, data show, too, that established software still has its limitations in judging blended emotions (Del Líbano et al. 2018).

In conclusion, although there is a variety of challenges for facial emotion recognition software, such software seems to work surprisingly well. Based on recent evaluations (Calvo et al. 2018; Del Líbano et al. 2018; Kulke et al. 2018) such software can be used in applied and scientific settings to reliably score facial emotion expression quicker, cheaper, and more objectively than with human FACS raters. And although there are still unresolved limitations, like the sole focus on 2D images and machine learning, recent approaches present ways to resolve these issues (Zinkernagel et al. 2018). Thus, presumably within the next few years, these limitations will have been overcome.

4.6 Current and Future Research

Recently, several studies (Calvo et al. 2018; Del Líbano et al. 2018; Hildebrandt et al. 2015; Kulke et al. 2018; Olderbak et al. 2014, 2021) have successfully introduced such software to answer basic and applied research questions. We will exemplify and highlight recent success with research on socio-emotional abilities. Socio-emotional abilities refer to human abilities related to interpersonal communication and action, including emotional abilities, such as emotion perception or regulation. Emotional abilities have also been categorized in the model of emotional intelligence (Mayer and Salovey 1997), which includes emotion perception, emotion expression, emotion understanding, and emotion management. Research mostly focused on receptive abilities, such as emotion perception and memory (Wilhelm et al. 2014). In order to measure such abilities, test takers are often asked to evaluate an item and choose amongst responses from a list of response options. Such receptive tasks ought to be distinguished from measures in which test takers create a response and the nature of that creation is the focus of evaluation. For example, productive measures have a long tradition in the measurement of written or spoken language proficiency (Reznick 1997). Often, performance evaluations for productive tasks are more difficult than assessing behavior in receptive tests, because defining a veridical answer to an item is more complex when the universe of possible responses is infinite. Nevertheless, if the goal is to evaluate aptitude and skill in emotion expression, we need productive tasks.

Novel technological developments allow assessing aptitude and skill in emotion expression by providing objective evaluations of facial expressions. We can now study how humans respond to specific forms of emotion elicitation and whether there are differences between subjects in these responses. We can now ask subjects to control their emotion expression and see how good they manage to do this. We can also ask participants to pose or imitate specific facial emotion expressions to study how good they do in deliberately using face expressions to communicate states (Hildebrandt et al. 2015). Beyond that, we can even study the dimensionality of typical facial expressions within persons to see what an individual's default expression looks like and to explore whether we find the same dimensions of typical emotion expression within and between subjects. We can even develop applications in which users respond with a landmark movement or an emotion expression rather than touching a device or responding verbally.

A prototypical procedure for studying such skills, aptitudes, or preferences could be that we ask test takers to react to emotion words (e.g. "happy") by producing corresponding facial emotion expressions. Likewise, we could ask them to react to a face by imitating its shown facial expression. A computerized evaluation of such expressions should proceed as follows. Presume a test taker is asked to express a happy face. The test-taker should receive a high score for an intense and prototypical happy expression, i.e. an expression that has a maximal probability to be recognized correctly by a random receiver. The evaluation is best accomplished if test takers are videotaped for a few seconds while they react to an item. Olderbak et al. (2014) discussed, how this data should be scored to represent expressive ability. Specifically, they recommend to first smooth the time series that could be based on AUs movements or represent emotion scores from readily available software produced by the computerized facial emotion expression recognition software and then extract maximum scores, as these represent this expressive ability (producing posed emotional expressions) with the least bias. This system is a sound way of scoring an emotion expression task and the procedures recommended here arguably offer a valid way of measuring abilities in the emotion expression domain.

How successful such a task can be applied was demonstrated in a recent study about individual differences in the ability to pose emotional expressions in psychopaths (Olderbak et al. 2021): Psychopaths are described to have improved lying and manipulation skills, such as emotion expression abilities. The study investigated this hypothesis with standardized emotion expression tests completed by incarcerated psychopaths, non-psychopathic inmates, and community volunteers. Against the expectations, psychopathy was negatively correlated with emotion expression abilities, but this deficit was completely explained by individual differences in general mental abilities in psychopaths.

Beyond posing emotions, the basic principles of such expression tests can be transferred to related fields. For instance, there is little research on emotion regulation ability employing actual ability tests, because evaluating the veridicality of a response to an emotion regulation item is complex. Just like with the posing of emotion expressions, we can ask test takers to regulate their facial expressions in different ways while experiencing emotional sensations. There are different ways to approach facial emotion regulation. For instance, we could provide strong stimuli to test takers and ask them to neutralize provoked expressions or to enhance the emotional response while they experience a congruent emotional sensation. In both cases, the evaluation of emotion expression should attempt to capture how successful test takers were in fulfilling the task (i.e. expressions under neutralizing instructions show no emotional expression beyond the baseline expression and enhanced expressions are strong in intensity and cannot be distinguished from authentic expressions).

4.7 Emotion Recognition Software in Mobile Devices

Apparently, emotion recognition software can easily be used in mobile devices, too. With constant improvements in the hardware of smartphones, alongside with increasing camera quality, the combination of mobile devices and computerized facial emotion expression recognition is an obvious and promising idea. An intriguing example for such applications was recently introduced by the artist Ruben van de Ven. Employing the Affectiva Software Developer Kit (Affectiva 2018), he developed the app Emotion Hero (van de Ven 2016a). In this gaming app, players practice and improve their facial expression skills by following instructions in a Guitar Hero-style fashion to facially express different emotions at varying time points and complex switches between emotions. The difficulty increases as the user progresses through levels and the app gives detailed individual feedback on how to improve facial expression in future rounds. Furthermore, players engage in a worldwide competition to become the ‘Emotion Hero’, motivating them to improve constant.

Although the app is primarily meant as an art project and “a playful invitation to open up the box of expression analysis to reveal the assumptions that underlie this technology” (van de Ven 2016b), we also consider it a serious option for intervention studies on emotion expression abilities. For example, a much discussed key symptom of autism is reduced emotion expression ability (Jaswal and Akhtar 2018; Olderbak et al. 2019). Combining gamification and extremely detailed feedback, ‘Emotion Hero’ or similar tools could be just the right intervention for people with autism. Via smartphones such an intervention is easily embedded in everyday life, data indicating change in the key symptom can easily be recorded, stored, and automatically analyzed.

Detailed and frequent observation via smartphones also lead to a rise of experience sampling studies in the last few years. Some prominent examples are studies using emotion adjective lists to track mood fluctuations within a day or week (Trampe et al. 2015; Wilt et al. 2011). Although this is an intriguing approach to explore time dynamics of emotion, employing self-report questionnaires always has the cost of biased data caused by a plethora of response biases. With computerized facial emotion expression recognition software, less biased approaches might be possible. Instead of asking participants in an experience sampling study to provide ratings for adjective lists, asking for a selfie or for permission to record audio or video from time to time might be the better way to gather ecologically valid data in a noninvasive way. Just as in ‘Emotion Hero’, these recordings could directly be analyzed in the smartphone and only emotion scores stored and sent to the researchers to adhere to privacy considerations.

4.8 Conclusion

In sum, we see great—and so far, untapped—potential in facial emotion expression recognition software. Clearly, evaluation of facial expressions is an incredibly useful tool for studying behavior, skills, abilities, and preferences that were not easy to assess before. The application with mobile devices additionally removes constraints of location, time, and context in which face identity and facial expressions are studied. Although there are still many options for improvement, such software has already proven to surpass average human performance in emotion recognition and is comparable to trained FACS raters. At the same time, such software offers a quicker and more economical way of obtaining insight into human emotional states. In addition, as the software is increasing in precision and as existing biases are reduced or eliminated, in a few years the software will likely surpass FACS raters' accuracy rates. Research that seemed impossible only a few years ago now gives the opportunity to test hypotheses about the very core of emotion and emotional abilities. As a result, new interventions facilitated by such software will hopefully improve the lives of many people.

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Chapter 5
An Overview on Doing Psychodiagnostics in Personality Psychology and Tracking Physical Activity via Smartphones Including Updates

Rayna Sariyska and Christian Montag

Abstract The aim of this chapter is to introduce and describe how digital technologies, in particular smartphones, can be used in research in two areas, namely (i) to conduct personality assessment and (ii) to assess and promote physical activity. This area of research is very timely, because it demonstrates how the ubiquitously available smartphone technology—next to its known advantages in day-to-day life—can provide insights into many variables, relevant for psycho-social research, beyond what is possible within the classic spectrum of self-report inventories and laboratory experiments. The present chapter gives a brief overview on first empirical studies and discusses both opportunities and challenges in this rapidly developing research area. Please note that the personality part of this chapter in the second edition has been slightly updated.

5.1 Introduction

With the rise of the digital era, human life is changing at a rapid pace (Scholz et al. 2018; Montag and Diefenbach 2018). Among others, this is mirrored in the growing use of portable devices such as laptops, smartphones, tablets and smartwatches. At the moment of writing this work, it is only 15 years after the introduction of the prominent iPhone, and in the meanwhile more than six billion smartphone subscriptions have been estimated worldwide (Statista 2022a). Mobile devices such as the smartphone do not only help us in dealing with manifold everyday life issues, but they also determine to a large extent how people communicate, work, and navigate themselves to new places.

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_5

With the development of the Internet of Things (IoT), different devices can be easily connected and help us to communicate or exchange data. For example, the companies Amazon and Apple introduced products, which enable their users to play music or prepare the grocery list via voice commands (e.g. Apple's HomePod with Siri and Amazon Echo with Alexa). In this context also the smart home needs to be mentioned, enabling humans to operate, e.g. the heating system in an apartment via the Internet. There are many other examples of concepts and devices which have partly been developed or are developing as we speak such as smart cars, smart factories, and smart cities (Forbes 2016). Without doubt, this development towards a totally interconnected world brings many advantages, but it also has its drawbacks such as ethical and privacy issues and high developmental costs. Moreover, the massive amount of data stemming from the interaction with the IoT needs to be saved on servers and only powerful computers can process the available data. Challenges with respect to privacy and ethical issues will be only shortly addressed in this chapter since they will be described in more detail in Chap. 2 by Kargl et al. and Chap. 3 by Dagum and Montag of this book.

To illustrate how the study of traces from the IoT can be useful in the field of psychodiagnostics, and, thus, in many research fields such as health psychology, clinical psychology, behavioural medicine, sociology, cognitive and sport sciences, this chapter will provide the reader with some examples from the literature. We will start with an overview of a relatively new branch of personality psychology trying to link smartphone use, including its diverse applications, to personality (Phan and Rauthmann, 2021). We will not refer to the many existing studies investigating smartphone use and addiction via self-report (Lachmann et al. 2017; Carvalho et al. 2018; Marengo et al. 2020), but will exclusively concentrate on works tracking the daily smartphone interaction directly via the smartphone and link this to self-reported personality measures. A second area to be reviewed will deal with physical activity, a variable being of more and more relevance in different areas of research such as health psychology and sport sciences (Mammen and Faulkner 2013; Verburgh et al. 2014; Blondell et al. 2014; Schuch et al. 2016).

5.2 Definition of Personality and the Big Five of Personality

Personality definitions vary depending on the large number of available theories. Many of those theoretical frameworks agree upon personality representing relatively stable individual characteristics in cognition, emotion and motivation resulting in behavioural outcomes, also known as *traits* (e.g. McCrae and Costa 1997). In contrast, *states* are, among others, defined as the momentary mood of a person (Montag and Reuter 2017; for a new debate on personality definitions see the work by Baumert et al. 2017). Montag and Panksepp (2017) emphasized the relative stability of personality over time and to a lesser extent across situations. Referring to the time component in healthy personality development, it has been widely accepted that personality stabilizes in early adulthood with slight changes towards "better" persons in terms of higher agreeableness and conscientiousness across the life span (McCrae and Costa 1994; also see studies by Helson et al. 2002 and Edmonds et al. 2013, reporting differences regarding the temporal stability of different personality traits and changes in personality throughout adulthood). For new insights into personality change we refer to a recent review-work by Bleidorn et al. (2018) and Bleidorn et al. (2020). With respect to discussions on personality stability across diverse situations, please see the important works by Mischel and Shoda (1995) and Mischel (2004), but in general also the important latent trait-state theory (Steyer et al. 1999).

Among the many personality theories, the Big Five of Personality without doubt represents one of the most well-established theoretical frameworks, which has been found to describe personality in many different countries and cultures and has been applied to different research topics (for an overview see Davis and Panksepp 2018; but also Montag and Elhai, 2019). The Big Five of Personality have been derived from a lexical approach with its early origins in the works of Cattell (1933), Allport and Odbert (1936), Fiske (1949) and Tupes and Christal (1992). The Five Factor Model of Personality formulating item sentences instead of relying "only" on adjectives to describe a person has been established by Costa and McCrae (1992); see also McCrae and John (1992). As a result of factorial analysis of human language with a focus on words describing persons, five factors appeared to describe personality: openness to experience, conscientiousness, extraversion, agreeableness and neuroticism (acronym OCEAN). High openness to experience is linked to curiosity and wide imagination, while conscientious people can be characterised by discipline, efficiency and reliability. Extraverts are energetic, outgoing and talkative. Agreeable people are generous and forgiving. Last, but not least, high neuroticism is linked to being anxious and tense (McCrae and Costa 1997). Please note that other taxonomies have been proposed going beyond the Big Five resulting in lower or higher number of factors to globally describe human personality. Perhaps of most relevance is the HEXACO model adding the dimension Honesty/Humility to the aforementioned Big Five factors (Ashton and Lee 2007). Personality traits have mostly been assessed via self-report inventories in the past. Therefore, we want to build an argument for the importance of also including directly observed behaviour to improve personality assessments in the next section.

5.3 On the Importance to Consider Directly Observed Behaviour in the Psychological Sciences

As mentioned, psychologists usually rely on self-report such as data collected via questionnaires or interviews, and comparably seldom on direct observation and implicit assessment methods (Paulhus and Vazire 2007; Baumeister et al. 2007). The examination of personality by means of self-report is very important and, in our opinion, will probably never be completely replaced by other research methods, since some information about a person might only be accessed via introspection

(Montag and Elhai 2019). This is also the case in other research areas such as clinical psychology, where it is of special relevance to gain insights into a person's subjective experience on his/her well-being by directly asking the patient. This said, there are a lot of complicated issues with self-report, which will be discussed in more detail later in this work. Before doing this, we mention that we will not discuss the advantages and disadvantages of assessing personality via questionnaires on smartphones. Such research including studies comparing the psychometric quality of data derived via online questionnaires compared with paper-pencil questionnaires have been conducted abundantly (see Riva et al. 2003; or Weigold et al. 2013).

The need to study and directly observe behaviour to get insights into the personality structure of a person has been put forward many times. Among others, Baumeister et al. (2007) highlighted the importance to assess behaviour in the field of personality and social psychology. The authors reported in their work the progression of observational studies published throughout the years: while at the end of the 70s around 80% of studies included behavioural variables, in 2006 less than 20% of the studies published in the *Journal of Personality and Social Psychology* considered behavioural variables. Baumeister et al. (2007) stressed that next to self-report measures, behaviour needs to be assessed too, since actual and hypothetical behaviour are known to differ to some extent (e.g. estimating one's own smartphone use compared to one's actual use results in different numbers, Montag et al. 2015a; see also a recent meta-analysis by Parry et al. 2021). One solution to reverse this trend in the literature would be the inclusion of variables tracked during human-technology interaction. Here, the smartphone possesses high potential to enable researchers to "participate" in the life of a study's participant by tracking the interaction with a smartphone on a daily basis. This will give insights into variables such as movement, interaction with others via calls or WhatsApp activity, and the frequency and duration of smartphone use in general. These variables are discussed to serve as markers of personality as will become evident in the reviewed works in one of the next sections.

5.4 Limitations of Self-report Assessment or Traditional Observation Methods

A large problem in research relying on self-report represents the tendency to answer in a socially desirable way, hence, to present oneself according to perceived social norms. Recall bias, or the difficulty to recall past events correctly or completely, is another problem often mentioned in this context. Moreover, self-report is often biased by impression management, self-deception and lack of conscious awareness (e.g. Paulhus and Vazire 2007).

With regard to traditional observation methods, standardised coding systems are often missing and this negatively impacts on inter-rater-reliabilities. Moreover, observer bias can negatively influence the quality of a study. Here, the expectations of the observer affect the way he/she perceives and evaluates the observed situation.

A further disadvantage of many observation studies is that they usually take place in a controlled environment, thus, it is seldom possible to observe participants' behaviour in their natural environment. This limits the generalizability and ecological validity of the results in such a study. Of note, observation is a very time-consuming method where often considerable resources need to be invested including the training of the observers. Last, but not least, both self-report assessment and traditional observations are difficult to conduct as a part of a longitudinal study given limited resources.

5.5 Overcoming Limitations of Self-report and Traditional Observation by Means of Smartphone App-tracking

Compared to self-report or observation methods, the inclusion of digital technology in modern research facilitates real-time monitoring of a person's behaviour in a naturalistic (real-world) setting, thus, fostering ecological validity. Bidargaddi et al. (2017) defined digital footprints as "… data traces arising as a by-product of individuals' day-to-day interactions with mobile and/or Internet-connected technologies …" (p. 165). These digital footprints can be utilized to get insights in many variables via digital phenotyping or mobile sensing (e.g. Lane et al. 2010; Bidargaddi et al. 2017; Insel 2018; for an early definition of the Digital Phenotype see Jain et al. 2015). Such research activities could be seen as part of a new interdisciplinary research area called Psycho(neuro)informatics (Yarkoni 2012; Montag et al. 2016; Montag 2019). Examples for digital footprints are online traces left by (credit) card payments, data collected with wearable technology devices such as smartwatches, rings and glasses, with smartphones and tablets, and technology used as a part of a smart home or Facebook "likes" and even profile pictures on social media (Bidargaddi et al. 2017; Marengo et al. 2021; Marengo et al. 2022; see also Chap. 8 by Marengo and Settanni exclusively dealing with psychodiagnostics using data from social media platforms). For the present chapter, we mention the smartphone as an important source, because it is usually connected to the Internet and has powerful integrated sensors and features including Bluetooth, GPS, microphone, accelerometer, WiFi, light sensor, and proximity sensor, all of high relevance to study a myriad of variables (Miller 2012; Harari et al. 2016).

Due to the opportunity to record behaviour via a smartphone on repetitive occasions and to track many different behaviours at the same time (e.g. tracking calls and social network activity), human behaviour and related personality traits can be described in a more fine-grained way. This not only enhances the precision of results, but also improves research dealing with stability issues of behaviour (Allemand and Mehl 2017). Further advantages can be named: assessments via smartphones are usually passive and unobtrusive, since many smartphone applications record the interaction with the smartphone in the background. Digital tracking methods might also in particular be well suited to capture the behaviour of young children and ageing adults who cannot provide reliable self-report (Allemand and Mehl 2017). Due to the wide availability and acceptance of smartphones, it is easier to recruit large and representative samples compared to the pre-smartphone-era. Moreover, due to the affordability of this technology for masses, such digital assessments can take place at relatively low cost. However, the development of a smartphone application to track behaviour is still costly and brings ongoing efforts to always smoothly operate on the newest platform versions. The recent years have also seen a strong trend to track biological variables, using wearables, such as electrodermal activity, pulse, blood pressure, even headbands for recording EEG parameters. These biological variables can be brought together with the behaviour of a person recorded via a smartphone or another mobile device (for a discussion on digital biomarkers see Montag et al. 2021b and chapter 31). Additionally, some applications are able to track users' subjective experiences through integrated questionnaires on the smartphone, next to the interactions with the smartphone (Montag et al. 2019). In so far, also the more classic method of "experience sampling" can be added to research in Psychoinformatics.

5.6 Examples for the Use of Smartphone Applications and Sensors to Assess Personality

In the following, results from studies showing associations between self-reported personality and (passively) recorded smartphone data will be presented. This also will provide first insights into the feasibility of personality assessment using smartphones via digital traces left as a side product of the daily smartphone interaction. Ultimately, researchers wonder if robust links between personality and certain patterns of smartphone interaction exist. Does knowledge about such patterns alone provide insights into the personality of a person? When interpreting the results from the following studies it is important to bear in mind that in most of the empirical works objectively measured smartphone use was correlated with self-reported personality, which might be biased, and, thus, not mirror the "true" personality of a person, as described in the previous sections.

De Montjoye et al. (2013) tested 69 participants with an open sensing framework on Android smartphones. Among others, calls and messages were recorded (please refer to Table 1 in the article by de Montjoye et al. (2013) for an overview of examined parameters) and personality was assessed with the Big Five Inventory BFI-44. By applying a classification method, the authors were able to predict personality variables (high vs. average vs. low scores) with accuracies varying between 49 and 61%. Even though these prediction rates are not very high, the results still suggest a link between smartphone logs and self-reported personality.

Chittaranjan et al. (2013) presented data from 117 participants tracked for the duration of 17 months. Regarding the data collection, among others SMS logs, call logs and app logs were examined. Positive associations between extraversion and the duration of incoming calls, and negative correlations between conscientiousness and the usage of video/music apps were reported (those are only a few examples from this study, many more associations were reported). Moreover, the authors demonstrated that a set of smartphone variables might be able to predict different personality traits (in particular, based on the smartphone data it was possible to classify users into groups of high vs. low on a personality trait). However, it needs to be mentioned, that the associations found were rather weak.

The link between extraversion and call variables, reported by Chittaranjan et al. (2013) was supported in two independent studies by Montag et al. (2014, 2019). In those two studies participants from Germany were tested using an application called *Menthal* for the duration of four weeks and the NEO-Five-Factor Inventory (NEO-FFI) in Montag et al. (2014), and another smartphone application called *Insights* for the duration of 12 days and the Trait Self-Description Inventory (TSDI, see Olaru et al. 2015) to assess personality in Montag et al. (2019). Nearly all investigated call variables (e.g. number of calls, duration of calls) were positively linked to extraversion. Conscientiousness was positively linked to the duration of calls in Montag et al. (2014) and neuroticism was negatively associated with the number of incoming calls in Montag et al. (2019). Moreover, Montag et al. (2014) reported excellent reliabilities of the tracked variables (calls) for the period of four weeks, which indicates that call behaviour is a stable variable on the phones and that a few weeks/perhaps even few days of tracking might provide already sufficient insights into call behaviour.

Stachl et al. (2017) also demonstrated a positive association between the frequency of calls, recorded on a smartphone for 60 days, and extraversion. However, extraversion was negatively linked to the duration of calls (non-significant association). Furthermore, positive associations between extraversion and application use related to photography and communication were reported. Regarding agreeableness, a positive relation with the use of transportation apps was reported, while conscientiousness was linked to lower use of gaming apps.

In another study, Montag et al. (2015b) addressed the role of social networking channels used on the smartphone. Here, 2418 participants with an average age of 25 years were tracked using the same *Menthal* application, introduced earlier in this section, for the duration of four weeks (for more information on the actual data analysis see the original work). Participants received feedback regarding their smartphone use (e.g. duration of smartphone use per day or most frequently used applications) through the *Menthal* application as an incentive for their participation. Self-reported personality data was collected with the ten-item version of the Big Five Inventory (BFI), integrated in the app. Results showed that participants spent 162 min per day on average on their smartphones, with about 20% of this time dedicated to WhatsApp use (ca. 32 min per day) and with less than 10% (ca. 15 min) dedicated to Facebook use. Additionally, results showed that younger age and the female gender were linked to longer WhatsApp use. With respect to personality, extraversion was positively and conscientiousness negatively associated with the duration of WhatsApp use. Similar, but weaker patterns could be observed for the duration of Facebook use. Again, the observed associations were rather weak.

Xu et al. (2016) investigated the installed apps on the smartphones of 2043 users and their relation to personality traits. Personality was assessed using the Big Five 44 questionnaire. Among others, it was demonstrated that high extraversion was negatively linked to installed apps in the gaming category and high neuroticism was positively associated with the adoption of photography and personalization apps. Moreover, high conscientiousness was negatively linked to the installed apps in the categories music and video, photography and personalization. While agreeableness was negatively linked to the adoption of personalization apps, openness to experience was not associated with any of the installed app categories.

Sariyska et al. (2018) demonstrated the use of the *Insights* smartphone application, mentioned earlier in this section, for personality-genetic research. In total, 117 participants were tested and smartphone data was recorded for 12 days. Among others, the association between a functional single nucleotide polymorphism (SNP) on the OXTR gene (rs2268498) and diverse smartphone-recorded variables was examined. The results demonstrated that the TT genotype (linked to higher empathy and better abilities in face recognition in previous studies, see Melchers et al. 2013; Christ et al. 2016), was associated with higher number of active contacts (contacts that one is in touch with as opposed to the total number of contacts in the phone book). Please note that this association got weaker after age was controlled for. Moreover, the variable active contacts was positively linked to extraversion. This study further demonstrated, how personality variables recorded using the methods of Psychoinformatics might be further used in the field of molecular psychology, the latter being a field aiming to understand the molecular (genetic) basis of individual differences in psychological variables (Montag 2018a, b). The feasibility to use smartphone recorded data in neuropsychological studies was also demonstrated in a study by Montag et al. (2017), where Facebook use (e.g. higher frequency of use per day) was associated with smaller grey matter volume of the nucleus accumbens, a brain region which is part of the reward system. In sum, both molecular-genetic and brain-imaging variables have been successfully investigated in the context of smartphone-tracked real-world behaviour. Indeed, the fusion of bio- and med-tech might become an important research avenue in the near future (Montag and Dagum 2019; see also a more recent review on this topic by Montag et al. 2021c and Montag et al., 2022).

In sum, the results of these studies indicate a link between objectively measured smartphone use and self-reported personality. Among others, the link between extraversion and call variables, recorded on the smartphone, was reported in a couple of independent studies, all using different self-report measures of personality. Thus, even after taking into account that self-reports might be possibly biased, the reported results strongly suggest an association between being extraverted and calling behavior. Moreover, app usage (e.g. social networking apps such as WhatsApp) seem to be linked to personality, too (for a meta-analysis on links between digital footprints of Facebook and personality see Marengo and Montag, 2020). It is important to bear in mind that most of the associations cited were rather weak. However, future studies need to address the question if a larger number of smartphone parameters taken together along with the use of machine learning approaches will be able to predict personality with a higher accuracy. This would not mean that digital traces can completely replace self-report measures of personality, since the subjective experiences of a person can only be assessed using self-report. However, depending on the study design and research question, objective measures derived with smartphones might complement self-report measures or even be more suitable in longitudinal designs where behavior is easily passively recorded and at a lower cost.

As mentioned in the abstract, we slightly updated the personality section of this article for the second edition to provide readers new insights into this dynamic research field. Beyond this, we also want to mention that several new interesting studies have been published linking smartphone log data to personality, which are relevant additions to the literature (e.g. Beierle et al. 2020; Ruegger et al. 2020; Stachl et al. 2020). Despite the importance of this line of research - namely linking self-reported personality to smartphone log data - we want to shortly reflect on a different avenue in personality science at the end of this section. In this realm, Montag et al. (2021a) mentioned that the study of digital footprints might yield in the near future a different personality taxonomy than the earlier explained Big Five. The Big Five have been carved out via a lexical approach. So what kind of taxonomy arises when we rely on the study of digital footprints where the study of text represents just one part of the large amount of available data?

5.7 Examples of Studies Assessing Physical Activity

In the following, the feasibility to use smartphone applications to assess physical activity and the effect of interventions to promote physical activity using smartphone applications will be shortly discussed in order to give a second perspective on smartphone app usage in assessing behaviour. Please note that our target was not to provide an exhaustive literature review (a few very recent systematic reviews and meta-analyses are reported below), but to give an overview of the recent literature and, thus, provide examples for the viability to use smartphones for physical activity tracking and promotion.

The study of physical activity is of high importance, because it is linked to many different health benefits such as the prevention of heart disease. Moreover, physical activity increases muscular and bone health, and reduces the risk for diabetes and obesity (World Health Organization 2018a). Ischaemic heart disease and diabetes mellitus are among the top ten global causes of death for 2016 according to the WHO (World Health Organization 2018b). Before we provide an overview of relevant studies investigating physical activity with app technologies, we shortly introduce the concept of physical activity and how it is currently assessed.

Physical activity is defined as "any bodily movement produced by skeletal muscles that results in energy expenditure" and includes any activity as a part of leisure time (e.g. sports, exercise, playing, dancing), work (e.g. household chores, gardening) and transport (e.g. walking, cycling) (World Health Organization 2018a; Caspersen et al. 1985, p. 126). For definitions on different kinds of physical activity we also refer to an older work of Caspersen et al. (1985). According to the World Health Organization (World Health Organization 2018a) globally 81% of adolescents aged 11–17 and 23% of adults at 18 years of age or older showed insufficient physical activity in 2010.

For adolescents the WHO recommended 60 min of moderate to vigorous physical activity per day, whereas for adults a minimum of 150 min of moderate-intensity or 75 min of vigorous-intensity physical activity per week are recommended. Guthold et al. (2018) reported levels of insufficient physical activity between 2001 and 2016, in a study including 1.9 million adult participants from 168 countries. The percentage of insufficient physical activity in 2016 was estimated 27.5% globally, with women (compared to men) and high-income countries (compared to low-income countries) demonstrating higher levels of insufficient activity according to the WHO guidelines. Althoff et al. (2017) conducted another large-scale study, including more than 700.000 participants from 111 countries (some of the analyses were conducted with only 46 countries). However, in this study physical activity was assessed using smartphone accelerometers as compared to the above study, based on self-report measures (accelerometers are sensors that measure the acceleration of a moving body, which can be applied to assess physical activity variables such as the number of steps per day; Evenson and Terry 2009). Some of the findings with regard to cross-cultural and gender differences were similar to those, reported by Guthold et al. (2018), thus, demonstrating similar results across different methods.

The WHO is giving advice on how to increase physical activity as presented in *The Global Action Plan for the Prevention and Control of Noncommunicable Diseases 2013–2020* and *The Global Action Plan for Physical Activity 2018–2030*, where a road map and guidelines have been developed, including policy recommendations for increasing physical activity on a global and national level. Similar to the problems reported regarding self-report measures of personality assessment, over- and underestimation of physical activity in self-report has been demonstrated as compared to objective measures such as accelerometers, pedometers or heart rate monitors (e.g. Prince et al. 2008; Adamo et al. 2009).

Due to the high penetration rate of smartphones in many societies around the globe, it is meaningful to assess their potential in promoting physical activity in this context. Seifert et al. (2017) demonstrated in a representative sample from Switzerland ($n = 1013$) that 20.5% of participants older than 50 years used mobile devices to track physical activity, thus showing that such devices are even used by a substantial amount of people in the higher age range. Among those participants, 55.1% used tablets or smartphones to track physical activity, while 6.1% used smartwatches and 38.8% used activity trackers. However, when comparing a group of participants tracking their physical activity with those who did not, it was demonstrated that the first group of participants was younger, was more involved in physical exercise and was more often male than female. Thus, such potential differences need also be considered as confounding factors in future research.

Regarding physical activity research Bort-Roig et al. (2014) conducted a systematic review, including articles published between 2007 and 2013, and reported a varying measurement accuracy of physical activity assessment via smartphones. In this study accuracy varied between 52 and 100% (please note that physical activity data here included findings from studies using accelerometers built in the smartphones, as well as external measurement devices, connected to the smartphone). Lu et al. (2017) demonstrated the feasibility to use smartphone accelerometers for tracking different types of physical activity such as daily living activities (e.g. walking, jogging, sitting and standing) and sports activities (e.g. race walking and basketball playing). Höchsmann et al. (2018) tested the accuracy of step counting for different smartphones and activity trackers in 20 participants in a laboratory setting (on a treadmill) and in a "free-walking" condition, and compared the results with video recordings. It was demonstrated that smartphone accelerometers (in particular the iPhone SE) accurately recorded the number of steps independent of their body position (in the pocket or bag) or walking speed in the laboratory condition, while they tended to slightly underestimate the number of steps in the "free-walking" condition. However, different levels of accuracy were reported for different smartphone brands (e.g. iPhone SE with Apple Health vs. Samsung Galaxy S6 Edge with Samsung S Health). Different accelerometer applications (not built in, but installed on the smartphone in this case on the iPhone SE; e.g. Runtastic Pedometer, Accupedo and Pacer), were also evaluated and all showed high accuracy for step counting. Hekler et al. (2015) focussed on the evaluation of Android smartphones (HTC MyTouch, Google Nexus One and Motorola Cliq) for physical activity tracking as compared to an Actigraph (an accelerometer-based activity/sleep monitor by the company Actigraph) in a laboratory setting (15 participants) and a "free-living" setting (23 participants). Different activities were assessed such as sitting, standing, walking with different speeds and bicycling. For the laboratory setting correlations between 0.77 and 0.82 between the Actigraph and the smartphones were demonstrated (these correlations got stronger when bicycling and standing were excluded). The correlations in the "free-living" setting were weaker, and varied depending on the intensity of the activity (0.38–0.67). In sum, these results suggest that smartphones offer a promising way to assess physical activity as their measurement accuracy is comparable with the accuracy of devices used by researchers in the laboratory. Last but not least, due to the opportunity to connect to the Internet via the smartphone, the smartphones' reasonably big displays, and features such as microphone and a speaker, smartphones can be used to provide feedback and motivate humans to actively engage in physical activity. Thus, smartphones have a large potential also as intervention tools.

It is noteworthy that first scientific evidence supports the idea that smartphone-based interventions are effective in increasing physical activity. Coughlin et al. (2016) conducted a review to evaluate the efficacy of different smartphone apps to promote physical activity and to lose weight. The review included six qualitative studies as well as eight randomized control trials. Here, mostly positive effects of the use of smartphone applications in promoting physical activity and reducing weight were reported (for effect sizes please refer to the individual studies reviewed in the article). In a recent meta-analysis Romeo et al. (2019) examined six randomized control studies on the influence of physical activity apps on objectively measured steps per day. Even though the intervention groups demonstrated increased activity in steps, the difference to the control groups was not significant. However, it was demonstrated that shorter interventions (< 3 months) and the sole focus on physical activity without considering further health benefits were more effective than longer interventions and additionally targeting diet. Overall, more research is needed on the effectiveness of physical activity interventions using smartphones. Moreover, the implementation of psychological theories which incorporate techniques for behavioural change, such as the Social Cognitive Theory, at the basis of functioning of the app interventions might help to enhance the effectiveness of such interventions (see Chap. 20 by Baumeister et al.). Some examples of such techniques include features allowing to monitor one's own activity or compare it to others, or to gain social support by sharing one's own achievements via online social networks (for an overview of theories on behavioural change and their current application in the realm of activity tracking please refer to Sullivan and Lachman 2017). Such features might not only support the behavioural intervention, but also seem to be facilitating factors for the use of smartphone accelerometers in the first place as reported in the review by Bort-Roig et al. (2014).

Last but not least, the link between personality and physical activity has been of interest for researchers to predict levels of physical activity, participation in different kinds of sports, and to answer the question of what distinguishes competitive sportsmen from amateur athletes, to name a few (e.g. Malinauskas et al. 2014; Wilson and Dishman 2015; Monasterio et al. 2016). By collecting further evidence on the link between those variables, smartphone interventions can be organized in a tailor-made manner, meaning that different strategies for promoting physical activity will be applied, e.g. with highly extraverted individuals as compared to highly neurotic individuals.

The availability and affordability of smartphones as well as the positive user attitude towards smartphones offers a large potential for smartphones as measurement tools and their role in intervention studies. However, there are also some drawbacks, which will be discussed in the next section.

5.8 Challenges and Further Implications

In the following, the challenges of smartphone tracking devices will be discussed and further implications will be drawn (see Table 5.1). One important issue to tackle in the near future to successfully implement smartphone technologies in research might be low compliance on the side of participants. Moreover, through the minute-to-minute tracking of different activities on the smartphone, participants might feel observed and might also try and adapt their behaviour (e.g. spent less time on Facebook; see also Montag et al. 2016). This falls in the context of social desirability, as discussed at the beginning of this chapter. A second concern is related to privacy issues and ethical considerations. Since tracking one's interaction with a smartphone can be described as an invasion of privacy, it is very important to ensure high levels of security when transferring the data from the phones of participants and storing them on a server (for an infrastructure of such a set up see Markowetz et al. 2014). Here, it should be also considered not to track everything what is possible, but ask (a) what variables do I really need to record to answer the research question at hand and (b) on what granularity level needs this behaviour be recorded? This all is of tremendous relevance to increase trust in a research project and elevate participation rates. Again,

Table 5.1 Overview of the challenges and future tasks of app tracking in research

Challenges of app tracking	Future tasks
Sensitive data and low compliance	Exhaustive information about the study design, to be collected data, where data is saved and how it is processed, who has access to data and what happens after data collection is finished
Privacy issues	See Chap. 2 of this book for a detailed overview on privacy issues
Ethical considerations	See Chap. 3 of this book
No official standards of use and data collection	Develop standard operating procedures (SOPs) in an interdisciplinary setting
Missing information on the reliability and validity of variables assessed with a smartphone application	Execution of "proof of concept" studies and development of SOPs based on the results of those studies
(Naturally) limited researcher's skill set regarding data analyses	Interdisciplinary cooperation and knowledge exchange
Precision of assessing a certain variable	Use of multiple parameters and combination of smartphone assessment with physiological data collection using wearable technology
High costs of developing such tracking applications	Consider the advantages of mobile tracking together with a reduction of costs in other areas such as for the administration of paper-pencil questionnaires or for staff to test participants on multiple occasions on site; moreover app tracking technologies are getting more affordable (see also Montag et al. 2019)
Reachability of participants who do not own a smartphone	Growing number of smartphone owners worldwide. Consideration of statistics for the particular country when representative studies are to be conducted using smartphone applications
Restrictions to a specific operating system such as Android	Development of applications that support all or most used operating systems; in addition a new work suggests that differences in certain variables across used operation systems are rather low. (Götz et al. 2017)

we will not go into detail on this topic because privacy issues and ethical concerns are addressed in Chap. 2 by Kargl et al. and Chap. 3 by Dagum and Montag.

There are also challenges to be met concerning a researcher's skill set. In psychological sciences, researchers so far seldom have the know-how to develop a smartphone application or use smartphone sensors to track behaviour. Thus, technical advice from a computer scientist is usually needed regarding hardware and software requirements, because large amounts of data are saved and processed. Moreover, the researchers might benefit from training in screening, organising (e.g. defining variables) and analysing big data, so that it can be interpreted in a meaningful way. Classical statistical approaches such as descriptive or inferential statistics might only superficially grasp what actually could be found in a data set. New analysis techniques from the computer science including machine learning clearly might be of advantage in Psychoinformatics. For example, by using deep learning approaches on large data sets one can achieve astonishingly accurate predictions/classifications comparable to those achieved by humans (e.g. Ronao and Cho 2016). These sophisticated methods have a tremendous potential to be used in research in general, but especially in fields such as health and clinical psychology as well as medicine, where accurate prediction or classification of e.g. symptoms is the foundation for successful prevention and intervention (Obermeyer and Emanuel 2016).

Additionally, the costs for the development of app tracking technologies are considerably high. However, in the long run the costs in other related research areas are tending to get lower, e.g. one has no costs for the administration of paper-pencil questionnaires or achieving a high sample size when conducting longitudinal studies.

In a still young research field such as Psychoinformatics, researchers need to ensure that their developed applications are reliable and valid measures of concepts such as emotion, personality or physical activity. In so far, the next years will surely see much research with “proof of concept studies”. Moreover, standard operating procedures (SOPs) for app tracking need to be developed (e.g. How many days of recordings are necessary to guarantee a reliable measure?). An additional drawback for researchers is that not everyone owns a smartphone yet and that there are considerable differences in the number of smartphone owners in different countries (Sullivan and Lachman 2017). Thus, this might hamper the recruitment of representative samples. However, this will likely change very soon, because penetration rates of smartphones are growing at a rapid pace. In Germany alone about 75 million users were estimated to use a smartphone in 2022 (Statista 2022b).

An important issue to be dealt with also concerns the precision in assessing a certain variable. As can be seen from the aforementioned reviewed personality studies, associations between personality and smartphone variables are currently moderate at best, and certain characteristics can be predicted better than others. In the literature reviewed earlier in this chapter, it is the link between extraversion and different smartphone variables that stands out, while the association with other personality dimensions was demonstrated less often. This inherently makes sense, because the smartphone or social media applications are often used to communicate with other persons, hence such variables tap in the social aspects of personality most strongly anchored in extraversion (see also the Chap. 8 by Marengo and Settanni). In sum, it is important to deal with the question what variables of the rapid developing IoT are of largest importance to best capture the manifold existing (psychological) variables (see also Montag and Elhai 2019)? Again, we stress the importance to think about how smartphone-based assessments can be accompanied by wearable devices collecting physiological data (biosensors for neural activity, heart rate variability and skin conductance such as smartwatches, shirts/shoes/socks with sensors or a headband to record EEG; see Malhi et al. 2017). Ultimately, it would be best, if one device could capture most of what is needed for the research question at hand. For a summary of propositions about implementation of psychological theories in smartphone-based research, study design and types of smartphone data necessary to test a particular hypothesis, we refer to the review by Sullivan and Lachman (2017) and to the article by Harari et al. (2016).

5.9 Summary and Conclusions

In sum, smartphones can be considered a valuable addition to the toolbox of personality psychologists, but also in other research areas such as health psychology or sport sciences to track physical activity. Their potential in research is yet to further unfold and for this to happen multidisciplinary collaborations are needed.

Conflict of Interest Christian Montag mentions that he received funding from Mindstrong Health for a project on digital phenotyping. Beyond that he serves as scientific advisor for Applied Cognition, Redwood City, CA, USA. This activity is financially compensated.

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Chapter 6
Smartphones in Personal Informatics: A Framework for Self-Tracking Research with Mobile Sensing

Sumer S. Vaid and Gabriella M. Harari

Abstract Recent years have seen a growth in the spread of digital technologies for self-tracking and personal informatics. Smartphones, in particular, stand out as being an ideal self-tracking technology that permits both active logging (via self-reports) and passive tracking of information (via phone logs and mobile sensors). In this chapter, we present the results of a literature review of smartphone-based personal informatics studies across three different disciplinary databases (computer science, psychology, and communication). In doing so, we propose a conceptual framework for organizing the smartphone-based personal informatics literature. Our framework situates self-tracking studies based on their substantive focus across two domains: (1) the measurement domain (whether the study uses subjective or objective data) and (2) the outcome of interest domain (whether the study aims to promote insight or change in physical and/or mental characteristics). We use this framework to identify and discuss research trends and gaps in the literature. For example, most research has been concentrated on tracking of objective measurements to change either physical or mental characteristics, while less research used subjective measures to study a physical outcome of interest. We conclude by pointing to promising future directions for research on self-tracking and personal informatics and emphasize the need for a greater appreciation of individual differences in future self-tracking research.

Keywords Self-Tracking · Smartphones · Mobile sensing · Personal informatics

The tracking of physical (e.g., weight, physical activity) and mental (e.g., mood, stress) characteristics has long fascinated individuals and scientists alike (e.g., Li et al. 2010; Wolf 2010). The practice of self-tracking involves a process of "…collecting data about oneself on a regular basis and then recording and analyzing the data to produce statistics and other data (such as images) relating to regular habits, behaviors, and feelings" (Lupton 2014, p. 1). According to the Pew Research Center,

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_6

a recent national survey of adults in the United States found that nearly 69% of American adults track at least one health-related physical characteristic or behavior (e.g., weight, diet, sickness symptoms, exercise routine), and that individuals with chronic health conditions were more likely to track such behaviors compared to healthy individuals. Among the self-trackers, approximately half reported recording their histories "in their head" (49%) and reported using notebooks or digital technology to record their physical health behaviors (55%; Fox and Duggan 2013).

The practice of self-tracking is typically associated with the goal of inducing behavior change through self-insight and self-monitoring (Kersten-van Dijk et al. 2017). That is, most individuals track their behaviors with the intention of changing unhealthy patterns and improving upon their general well-being. Today, the advent of ubiquitous sensor-driven technologies (e.g., smartphones, wearable devices) has revolutionized the way individuals self-track their physical and mental characteristics, and how they interact with personal informatics in general (e.g., Swan 2012).

6.1 Personal Informatics and Self-tracking Technologies

Personal informatics (PI) broadly defines a set of self-tracking technologies that help individuals collect and reflect on personal information (Li et al. 2010). Self-tracking technologies include diverse forms of digital technology, such as web-based applications (i.e. Mint Financial planner), wearables (i.e. Apple Watch, Nike + Band), mobile phone applications (i.e. WeRun; Li et al. 2010). Personal informatics systems operate under the pretext of three interrelated goals (Kersten-van Dijk et al. 2017): (a) to accurately measure the target domain (e.g., physical behaviors, mental states) using data produced from the use of digital technology, (b) to produce meaningful analysis of this data and (c) to communicate this analysis to the user in a comprehensible manner.

Past research has compared two working models of personal informatics (Kersten-van Dijk et al. 2017). The first model is a stage-based model consisting of distinctive consecutive states: preparation, collection, integration, reflection, and action (Li et al. 2010). The reflection stage constitutes periods of self-reflection resulting from the use of PI systems, which leads users to change their behavioral trajectories after self-reflection. The second competing model maintains that the use of PI systems is too continuous to be discretely modeled in a stage-wise manner because participants using personal informatics systems often simultaneously engage in the activities described in the discrete stage model (Epstein et al. 2015). For example, the collection of self-tracking data usually occurs in conjunction with processes of self-reflection, as participants' experience of self-tracking induces them to reflect on their behavioral patterns. Despite their differences, both models of personal informatics (Li et al. 2010; Epstein et al. 2015) converge on the idea that behavior change is the ultimate outcome of an engagement with personal informatics systems (see Kersten-van Dijk et al. 2017 for complete review and comparison of both models).

The use of self-tracking technologies in daily life is likely to continue increasing at a rapid rate in the near future, as digital self-tracking is already becoming a pervasive and ubiquitous phenomenon (Paré et al. 2018). Thus far, the majority of commercial digital technologies for self-tracking target health and fitness as areas of application (e.g., Samsung Gear Fit, Apple Watch). Yet, digital self-tracking applications are accessible for none to marginal costs, and portable fitness hardware such as pedometers are relatively affordable (Rooksby et al. 2014). Moreover, scholars have collectively recognized the growing popularity of smartphone applications, wearable sensing technology, and other digital self-tracking platforms (Lupton 2013; Rooksby et al. 2014; Sanders 2017). And movements such as Quantified Self (2015) have developed a variety of digital technologies that facilitate the tracking of diverse behaviors (e.g., mobility patterns from GPS data; Parecki 2018).

Smartphones, in particular, stand out as a digital technology with much promise for self-tracking and personal informatics because they permit both active logging (via surveys) and passive tracking (via mobile sensing; Harari et al. 2017). Mobile sensing technologies permit the unobtrusive collection of data from mobile sensors and system logs embedded in the smartphone (microphones, accelerometers, app usage logs) to recognize human activity (e.g., sociability, physical activity, digital media use; Choudhury et al. 2008; Lane et al. 2010). By automating the continuous detection of a person's behavioral patterns and surrounding context (Harari et al. 2017b; Harari et al. 2018), mobile sensing is poised to play an important role in the development of effective personal informatics systems that induce positive behavior change. To examine the effects of self-tracking with smartphones in personal informatics, here we review and provide an organizing framework for existing and future scholarship on self-tracking research with mobile sensing.

6.2 A Framework for Self-tracking Research

We have two interrelated aims in writing this chapter. First, we aim to provide a review of the existing trends, gaps, and directions in the research literature on smartphones in personal informatics. We focus specifically on reviewing the existing literature that uses smartphone-based self-tracking technologies to collect user data (e.g., via self-report questions or mobile sensing), analyze user data, and/or that use the smartphone to communicate results aggregated from a variety of sources to the user. Given the interdisciplinary nature of self-tracking research and the variety of application domains into which smartphones have been deployed in personal informatics systems, we conducted our literature review across three databases selected to represent the primary disciplines engaging in such research: PsychINFO (representing psychology), ACM (representing computer science), and Communication and Mass Media Complete (representing communication). We note that nearly all of the articles that met our inclusion criteria were indexed in the ACM database, while our inclusion criteria yielded few articles from the PsychINFO and Communication and Mass Media Complete databases. We provide a detailed description of our literature review procedure in Table 6.1 (keywords used), Table 6.2 (derivation of keywords and their search arrangement), and Table 6.3 (filtering process). Additionally, Fig. 6.1 shows the number of search results returned at and filtered during the various stages of the filtration process .

Second, we aim to provide a conceptual organizing framework to situate the substantive contributions of past and future smartphone-based personal informatics research. We believe a framework is needed to help situate the contributions of a given self-tracking study within the broader literature with regard to its measurement and outcome of interest domains.

Table 6.1 Methodology of literature review

Mobile sensing keywords	Mobile sensing; mobile-sensing; mobile sense; smartphone sensing; smartphone sensing; smartphone sense
Personal informatics keywords	Self-monitoring; self monitoring; self-tracking; self-track; self tracking; self track; quantified self; life-logging; lifelogging; life logging; personal informatics
Behavior change keyword	Behavior change
Categorical keywords	*Physical activities* Physical health; Activity, walking, steps, sedentary; Running; Exercise, fitness, workouts; Illness, symptoms
	Physiological Physiological; Heart rate; Blood pressure; Nutrition; Food diet; Calories; Sugar intake; Water intake; Alcohol; Vitamins; Medications
	Sleeping patterns Sleeping patterns; Duration, Quality, Schedule; Rest
	Productivity Productivity; Study habits; Laziness; Focus; Time management, time spent working; School-life balance taking breaks; Academics; Class Schedule
	Mood Mood, Emotions; Depression; Sadness; Anxiety; Stress; Happy; Content; Relaxed; Relaxation; Anger; Curiosity; Kindness; Consideration; Positive Thoughts; Negative thoughts
	Socializing Socializing; Conversation Quality; Conversation Duration; People Spending Time With; Time Spent Alone; Dating, Romance; Social Media Communications
	Digital Media Use Digital media use; TV Time; Screen Time; Computer Use; Internet use; Phone use; Gaming; Social Media Use
	Daily Activities Daily activities; Hobbies; Reading; Learning; Location; Hygiene

Generally, existing research on smartphones in personal informatics has largely focused on describing the development, deployment, and effectiveness of individual personal informatics systems that measure different behaviors in a variety of contexts. Less is known about the substantive focus of these different studies, across different measurement domains (tracking of physical and/or mental characteristics) and outcome of interest domains (aiming to promote insight or change in physical and/or mental characteristics). To provide an organizing conceptual framework, we present a two-dimensional space that resembles the Cartesian coordinate plane (as shown in Fig. 6.2) that maps out four different quadrant areas representing the substantive focus of smartphone-based self-tracking research: (1) objective measurement—physical outcome of interest (e.g., measuring accelerometer to infer physical activity levels), (2) objective measurement- mental outcome of interest (e.g., measuring mobility data using GPS to infer depressed mood), (3) subjective measurement—mental outcome of interest (e.g., measuring self-reported experience sampling surveys to assess psychological states), and (4) subjective measurement—physical outcome of interest (e.g., measuring self-reported experience sampling surveys to assess subsequent changes in sensed physical activity).

To illustrate our framework's potential for conceptually organizing domains of interest in self-tracking research, we coded each reviewed article into one of the four quadrants based on its substantive research contribution with regard to its

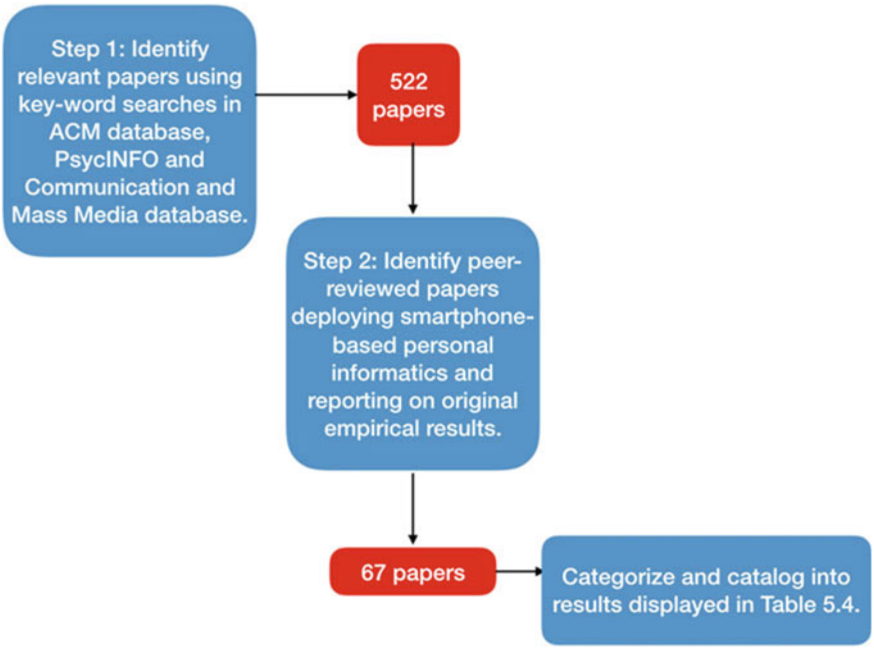

Fig. 6.1 Procedural flowchart and number of search results returned

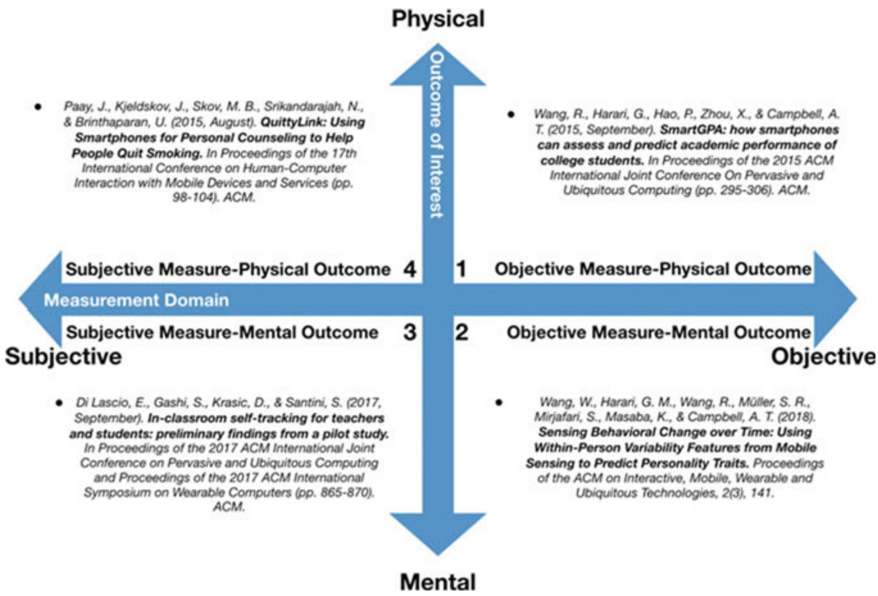

Fig. 6.2 Conceptual framework for organizing the smartphone-based PI literature. To organize the surveyed mobile sensing literature, we present a two dimensional conceptual framework. The conceptual framework resembles the Cartesian coordinate plane, consisting of two axis that encode magnitude relative to space. As shown in Fig. 6.1, the x-axis represents the measurement domain of the surveyed literature—specifically, it identifies the extent to a given article was focused on collecting either subjectively measured data (i.e. experience sampling surveys) or objectively measured data (e.g., mobile sensors). For instance, some papers described collecting physical activity data using the accelerometer (Wang et al. 2015), whereas others were focused on collecting mood or depression related information using phone-based ecological momentary assessments (Di Lascio et al. 2017). The y-axis represents the extent to which the researchers used their measurements to assess either physical or mental outcomes of interests. For instance, while some researchers were focused on using collected physical activity data to categorize various kinds of physical movements and social interactions (Harari et al. 2017b), others were focused on using physical activity data to infer mood or depression scores (Mehrotra et al. 2016)

measurement-outcome of interest domains. To verify the accuracy of our framework classifications, a research assistant independently coded the articles using the four quadrants as well. The classifications were then compared, and any discrepancies were resolved through discussion. The full results of the literature review are presented in Table 6.4.

Much of the existing research has focused on the different components or “stages” that are characteristic of personal informatics systems. Some studies were focused on developing high-accuracy activity classifiers from sensors embedded in smartphones and wearables (e.g., Madan et al. 2010), whereas others were anchored around creating optimal feedback systems that were effective at inducing behavior change (e.g., Bentley et al. 2013). Below we discuss the literature on smartphones

Table 6.2 Details of literature review

Procedure	Categorical keyword source
In order to determine the extant literature linking the themes of smartphone-based personal informatics and behavior change, we used the following formatting of keywords to return searches in each database: [mobile-sensing keywords separated by OR] AND [self-tracking keywords separated by OR) AND ["behavior change"] AND [coding category keywords]	The coding category keywords were extracted from another study in which student's responded to questions asking them about motivations to self-track different aspects of their lifestyle To conduct our literature review, we utilized categorical keywords that were extracted from qualitative responses that 1706 young adults provided to the following question: "What would motivate you personally to self-track, and which behaviors would you track?" The qualitative responses were content analyzed to obtain an exhaustive list of 75 individual self-tracking categories, which could be described by 8 broader categories (See Table 6.1 for the full list of categories): physical health, physiological, sleeping patterns, productivity, mood, socializing, digital media use, and daily activities Hence, we conducted the full literature review in eight stages, operationalizing one self-tracking category (with all of its individual sub-category topics) through our keyword patterns in each stage

in personal informatics, focusing our discussion of previous research based on the type of physical and mental characteristics being tracked (Table 6.4).

Physical Activity. Physical activity was the substantive focus of many of the papers we reviewed. The majority of studies on physical activity fell under either the objective measurement-physical outcome of interest or objective measurement-mental outcome of interest quadrants of our conceptual framework. For instance, Harari et al. (2017a) deployed a smartphone sensing application, StudentLife, which measured daily durations of physical activity using data collected from the accelerometer sensor of the smartphone in a college student population. Notably, the authors found that individual differences in ethnicity and academic class were predictive of changes

Table 6.3 Steps for filtering literature review results

Step No.	Description of filter
Step 1	The result must be a peer-reviewed paper and report on original empirical work
Step 2	The result must discuss at least one smartphone-based technology that supports a collection of human characteristics and/or acts a mediator of relevant feedback information on behavioral patterns

Note The smartphone or mobile may be involved either in the data collection stage or the feedback generation and communication stage of the personal informatics ecosystem deployed in physical activity. While Harari et al. (2017a) were not focused on the feedback component of personal informatics systems, other researchers were especially interested in developing an effective feedback system developed from the collected physical activity data in order to engage users in self-reflection. Kocielnik et al. (2018) developed Reflect Companion, a mobile conversational software that facilitated immersion in the reflection of activity levels as aggregated from fitness trackers. Their results indicated that mini-dialogues were successful in inducing reflection from the users, on their physical activity levels. Some studies were focused on using the personal informatics system to induce systematic behavior change that increases physical activity levels in individuals. To incentivize higher levels of physical activity, these studies gamified the objective of increasing physical activity by either individual into motivated competing teams (e.g., Ciman et al. 2016; Zuckerman and Gal-Oz 2014) or by tapping into their existing social networks (Gui et al. 2017).

A large majority of studies in this category were single deployment studies that examined the efficacy of personal informatics tools deployed to monitor physical activity. While some studies attempted to situate their work under a theoretical model of behavior change (e.g., Theory of Planned Behavior; Ajzen 1985; Du et al. 2014) virtually no research attempted to integrate with extant personal informatics models of behavior change such as those proposed by Li et al. (2010). Instead, different researchers tended to make use of different theoretical models of behavior change originating from a range of behavioral disciplines. For example, the Transtheoretical Model of Behavior Change (Glanz et al. 2008) and the Social Cognitive Theory of Behavior Change (Bandura 2004) have been employed in physical activity intervention studies (e.g., in the design of applications; Marcu et al. 2018). However, there is a general lack of integration between these theoretical models and personal informatics models of behavior change. Such an approach has led to some studies reporting conflicting behavior change outcomes and high participant attrition, which may be a result of using models of behavior change that are not specifically adapted to the use of personal informatics systems.

Physiological. There were only four studies that we categorized as pertaining to physiology in our literature search. Hwang and Pushp (2018) deployed a system called “StressWatch”, which was aimed towards assisting users in triangulating the sources of their stress in their daily life. Using a concert of smartphone and smartwatch systems, StressWatch monitored the context of users in concert with their heart rate variability. Subsequently, the StressWatch extracted stress levels from the heart rate variability data and “matched” these patterns with the changing contexts of the user in order to suggest possible origins of stress in daily life. In a single subject pilot deployment, the authors refined the design of StressWatch by deciding that stress levels could be accurately detected when eating and working, but not when walking.

In a similar line of work, Bickmore et al. (2018) developed a virtual conversational agent that counseled patients suffering from chronic heart condition atrial fibrillation using data collected from a heart rhythm monitor attached to a smartphone. In a randomized trial with 120 patients, the authors found that the conversational agents led to a significant positive change in the self-reported quality of life scores

Table 6.4 Overview of literature review results organized according to our framework

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
1. Objective Measurement—Physical Outcome of Interest										
Athukorala et al. (2014)	1								X	X
Bentley et al. (2013)	1	X		X						X
Bexheti et al. (2015)	1	X								X
Brewer et al. (2015)	1								X	X
Chen et al. (2016)	1	X		X				X		
Ciman et al. (2016)	1	X								X
Du et al. (2017)	1	X								X
Fang et al. (2016)	1	X								X
Fujiki et al. (2007)	1	X		X				X		
Gouveia et al. (2015)	1	X								X

(continued)

Table 6.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Grimes et al. (2010)	1	X		X						X
Gweon et al. (2018)	1	X							X	X
Harari et al. (2017b)	1	X						X		
Hirano et al. (2013)	1	X								X
Johansen et al. (2017)	1	X								X
Jylhä et al. (2013)	1	X								X
Kadomura et al. (2014)	1			X						
Kamphorst et al. (2014)	1	X								X
Ko et al. (2015)	1			X					X	X
Kocielnik et al. (2018b)	1	X								X

(continued)

Table 6.4 (continued)

References	Framework classification	Physical and mental characteristics								
		Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Lacroix et al. (2008)	1	X					X			X
Lee et al. (2014)	1	X	X	X						X
Lee et al. (2017)	1	X		X	X					X
Li et al. (2017)	1								X	X
Madan et al. (2010)	1	X		X				X		
Mollee et al. (2017)	1	X								X
Muaremi et al. (2013)	1	X		X						X
Pipke et al. (2013)	1									X
Rabbi et al. (2015)	1	X		X						X
Simon et al. (2012)	1								X	X

(continued)

Table 6.4 (continued)

References	Framework classification	Physical and mental characteristics								
		Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Tang et al. (2013)	1								X	X
Tulusan et al. (2012)	1					X				X
Van Bruggen et al. (2013)	1								X	X
Wang et al. (2015)	1	X								X
Weiss et al. (2012)	1					X			X	X
Zheng et al. (2008)	1									X
Zuckerman and Gal-Oz (2014)	1	X	X	X						X
2. *Objective Measurement—Mental Outcome of Interest*										
Abney et al. (2014)	2								X	X
Bai et al. (2013)	2				X			X		X

(continued)

Table 6.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Bickmore et al. (2018)	2	X	X							X
Canzian and Musolesi (2015)	2						X			X
Chaudhry et al. (2016)	2	X		X						
Cuttone and Larsen (2014)	2									X
Doryab et al. (2015)	2	X								X
Greis et al. (2017)	2								X	X
Huang et al. (2016)	2						X	X		X
Hwang and Pushp (2018)	2		X				X			X
Mehrotra et al. (2016)	2						X		X	X
Meyer et al. (2016)	2	X								X

(continued)

Table 6.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Wang et al. (2016)	2	X			X		X			
Wang et al. (2018a)	2	X					X			
Wang et al. (2018b)	2	X			X	X		X		X
3. Subjective Measurement—Mental Outcome of Interest										
Barbarin et al. (2018)	3	X		X						
Bentley and Tollmar (2013)	3	X			X		X			X
Di Lascio et al. (2017)	3					X	X	X		
Kuo et al. (2018)	3	X							X	X
Paredes et al. (2014)	3	X		X				X		
Sasaki et al. (2018)	3						X			X

(continued)

Table 6.4 (continued)

		Physical and mental characteristics								
References	Framework classification	Physical activity	Physio-logical	Nutrition	Sleeping patterns	Productivity	Mood	Socializing	Digital media use	Daily activities
Springer et al. (2018)	3						X			
4. Subjective Measurement—Physical Outcome of Interest										
Du et al. (2014)	4	X		X						X
Gui et al. (2017)	4	X						X		X
Hsu et al. (2014)	4	X		X						X
Kocielnik et al. (2018a)	4								X	X
Li et al. (2015)	4	X						X		X
Luhanga (2015)	4	X		X						
Marcu et al. (2018)	4	X								X
Möller et al. (2013)	4								X	X
Paay et al. (2015)	4	X								X

Table 6.4 shows the following information: (1) the quadrant of our self-tracking framework that references were categorized under and (2) the categories that were a focus of the specified references, as denoted by an "X" in the relevant columns

as compared to a control group who did not receive the agent-based counseling. Cumulatively, studies in the Physiology category provided promising avenues for detecting and modeling feedback based on real-time heart-rate data.

Nutrition. The large majority of studies on nutrition were categorized as objective measurement-physical outcome of interest quadrants of our conceptual framework. For example, Rabbi et al. (2015) developed and tested the efficacy of the MyBehavior application using the Theory of Planned Behavior (Ajzen 1985). MyBehavior was a smartphone application that integrated inferences of physical activity levels and dietary behaviors to produce personalized recommended changes to these patterns in order to promote a healthier lifestyle. The authors found that their personal informatics system led to an increase in physical activity and a decrease in food calorie intake, as compared to a control condition of participants not using the MyBehavior application. Other studies were focused especially on target populations—such as women suffering from obesity (Barbarin et al. 2018). Instead of implementing behavior change interventions directly, these studies were focused on identifying the unique needs of clinical populations.

Sleeping Patterns. The large majority of studies on sleeping patterns were categorized in either the objective measurement-physical outcome of interest or objective measurement-mental outcome of interest quadrants of our conceptual framework. Studies categorizing this theme are focused on assessing sleeping patterns from smartphone or wearable sensors and also on the digitized manual tracking of sleeping patterns, to delineate resulting changes in behavior. The emphasis individual studies place on different components of personal informatics varies. For instance, Bai et al. (2013) assessed changes in sleeping patterns using data collected from a mobile phone and through self-report surveys. They did not provide a feedback mechanism for participants, but instead used parts of the collected data to train their model on sleep-related habit formation patterns.

In contrast to this feedback-agnostic approach, Bentley et al. (2013) were exclusively focused on creating a tool to help individuals derive meaningful feedback from smartphone sensing data. The researchers constructed Health Mashups, a system designed to detect meaningful connections that are stable over time between a variety of behaviors and sensed data. One of these behaviors was sleep—the researchers collected sleeping pattern data from Fitbit. The researchers performed statistical analyses on the sleep data each night and then displayed natural language statements to individuals about observed associations (i.e. “On days when you sleep more, you get more exercise”) on their smartphones (Bentley et al. 2013). A comprehensive PI deployment, incorporating elements from both of the previously cited sleep-related studies, was performed by Lee et al. (2017), who developed a wearable and smartphone-based system to manage unconscious itching behaviors that occur while individuals slept. Developed over the duration of two experiments and deployed in a full pilot study, the Itchtector was deemed helpful by many of the participants in the study, as revealed through qualitative interviews.

Productivity. Research examining productivity in personal informatics systems is relatively sparse and focused on the objective measurement-physical outcome of interest, objective measurement-mental outcome of interest, and subjective measurement-mental outcome of interest quadrants of our conceptual framework. Di Lascio et al. (2017) refocused the attention of personal informatics from fitness and personal health onto the "work environment". The researchers identified broad aims that a Quantified Workplace personal informatics system would need to be designed to address: choosing valuable data sources, deriving insights relevant to the workplace from this data, and driving change from these insights. The researchers then implemented a personal informatics system in a university setting to explore potential answers to their three questions. A metric called the Emotional Shift was developed in order to assess changes in affective states over the course of a university lecture. The authors reported tracking this metric using the PI system to show how emotional trajectories manifest in a real-life productivity-based environment. Since these researchers relied on surveys to collect data to assess mood changes in a work environment, this paper fit into the subjective measurement-mental variable of interest quadrant of our conceptual framework.

Mood. The large majority of studies on mood were distributed over the objective measurement-mental outcome of interest and mental measurement-mental outcome of interest quadrants. Studies categorizing this theme typically relied on self-reported mood information at pre-specified daily frequencies to track individual trajectories of mood over time. For instance, the EmotiCal personal informatics system tracked mood and provided predictive emotional analytics to individuals with the intention of facilitating participant understanding of mood and "trigger events" (Hollis et al. 2017; Springer et al. 2018). The EmotiCal system also implemented a feature to generate remedial plans by recommending new behaviors with the aim of increasing positive emotion. The researchers found that mood forecasting improved mood and emotional self-awareness in comparison to control condition participants, implying that positive behavior change had occurred as a result of using the PI system. In another example, mood-driven PI systems deployed amongst targeted populations—such as bipolar patients—did not result in systematic behavior changes (Doryab et al. 2015). The researchers deployed the MONARCA system, which patients used to report their daily mood scores. Additionally, the MONARCA system was able to sense behavioral traces, and it aimed to identify the effect of specific behaviors on the daily mood scores. While the authors identified sleeping patterns and physical activity as the main drivers of mood, none of the 78 participants in the pilot deployment reported any mood improvements as a result of using MONARCA. The authors used their insights to develop a "mood inference" engine for the existing MONARCA app.

The majority of the studies categorized by this theme did not set out to induce and measure the behavior change resulting from the use of their platforms. This was a concern, as without such an approach, the efficacy of different mood-targeted personal informatics systems cannot be assessed. Moreover, there was a distinct absence of passive mood detection technologies— all the surveyed papers relied on participant input to collect mood-related information.

Socializing. The large majority of studies on socializing were distributed over the objective measurement-physical outcome of interest and objective measurement-mental outcome of interest quadrants. Studies categorizing this theme typically assessed sociability from existing online social networks or from the microphone contained in smartphones and attempted to relate variations in behaviors and traits to the observed variances in sensed sociability. For instance, Harari et al. (2017a) examined behavior change in sociability patterns amongst a cohort of 48 students that participated in a 10-week smartphone-sensing study. The results suggested that sociability was typically high during the initial weeks of a semester but then decreased during the first half of the semester as the midterm examination period approached. In the second half, sociability increased and individual differences in sociodemographic characteristics (ethnicity and academic class) predicted sociability trajectories during the semester.

In a similar line of work across the objective measurement-physical outcome of interest quadrant, Madan et al. (2010) investigated how health-related behaviors spread as a result of face-to-face interactions with peers, by deploying a mobile sensing study that collected relevant data about participant location and ambient conversation using the microphone. The researchers found that the health behaviors exhibited by participants were correlated with the behaviors of peers that they interacted with over sustained periods of time, and this type of sensing could be implemented using just the sensor technology already embedded in a smartphone. This work suggests that future behavior change interventions might benefit from relying on the sensing of social interactions, given the strengths of these technologies for passively and non-intrusively collecting data about interpersonal interactions as they unfold in the course of daily life.

Hence, studies categorizing this self-tracking theme were typically focused on detecting sociability from online social networks or through smartphone sensors, in order to assess how social trajectories manifest in an ecologically valid manner. Some studies were focused on examining the impact of this sociability on real-world habits and behaviors, including fitness and diet. Studies under this theme occasionally attempted to assess behavioral change quantitatively (for instance, see Chen et al. 2016) but a large number of studies did not aim to operationalize behavior change or failed to do so in a quantitative manner.

Digital Media Use. Studies on digital media use were distributed over the objective measurement-physical outcome of interest, and the objective measurement-mental outcome of interest quadrants. For instance, FamiLync is a self-tracking app designed to measure digital media use and abuse in collaboration with one's family (Ko et al. 2015). The app promoted the non-use of smartphones in certain settings, contained a 'virtual public space' which facilitated social awareness on the use of the smartphone and contained tools that discouraged or prevented the use of digital media technologies (i.e., locking the screen and snoozing social media notifications). A three-week user study spanning 12 weeks indicated that the app improved the understanding of smartphone usage behavior and therefore allowed for more efficient parental mediation of excessive digital media use. Such positive changes in digital media use are likely to boost the mental health of participants, as excessive or very frequent smartphone usage is shown to negatively influence mental illness (Choi et al. 2012). In a related approach that went one further step by operationalizing participant predictions of future behaviors, Greis et al. (2017) deployed a PI system that tracked the number of times individuals unlocked their phone on any given day. Participants were required to indicate how many times they predicted to unlock their phone on any given day during each morning of the study. The results indicated that the exercise of self-predicting future behavioral patterns led to the automatic discovery of new insights into patterns of smartphone use (Greis et al. 2017). Hence, while the literature on digital media use trackers is sparse, this is a particularly important area for PI deployment with past research showing that it is possible to obtain behavioral assessments of "smartphone addiction" tendencies from smartphone data (Montag et al. 2015). This seems like a promising direction for behavior change interventions given the adverse risks that excessive digital media use (e.g., smartphone or social media addiction) poses to developing adolescents and adults. The research reviewed here indicates that digital media use tracking PI systems may influence positive behavioral change through increased self-tracking habits that reduced usage through increased awareness of use (Greis et al. 2017; Ko et al. 2015).

Daily Activities. The large majority of studies on daily activities were distributed over the objective measurement -physical outcome of interest, objective measurement-mental outcome of interest, and subjective measurement-physical outcome of interest quadrants. For instance, Wang et al. (2018) investigated how patterns of behavior change in daily activities, as sensed through the smartphone, could be used to predict personality traits of young adults. Specifically, the researchers examined how trends in within-person ambient audio amplitude, exposure to human voice, physical activity, phone usage, and location data predicted self-reported Big Five personality traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness). Hence, this study fits into the objective measurement -mental variable of interest quadrant because it used data generated from physical measure (i.e., accelerometer data, microphone data) to make mental inferences (i.e., personality traits). The results indicated that personality traits could be modeled with high accuracy from these within-person variations in daily activities.

While Wang et al. (2018) did not overtly focus on administering feedback to individuals, Hirano et al. (2013) deployed a PI system with a focus on providing effective feedback to participants, specifically about their walking behavior. The researchers designed an app that detected participant motion, contained a manual digital logging feature of daily step count, and regularly notified participants to engage in physical activity. The researchers found that participants reported becoming more self-aware of their bodies and were wary of the time they spent sitting.

Some studies examined how daily activities are indicative of personality traits and mental states. For instance, one mobility study, focused on target populations of depressed individuals, succeeded in predicting depression states from mobility data of participants (Canzian and Musolesi 2015). Other studies developed and tested the efficacy of developing feedback techniques that nudge users towards engaging in healthier physical routines during their daily activities (i.e., Hirano et al. 2013). While the reviewed work suggests that daily activity PI systems can induce self-insight and self-awareness (e.g., Hirano et al. 2013), the effects of these systems on behavioral change outcomes remain relatively under-investigated and ambiguous.

6.3 Discussion

In this chapter, we surveyed the existing literature to identify an organizing framework for situating past and future scholarship using smartphones in personal informatics research. Our review findings suggest that a two-dimensional conceptual framework can be used to organize the smartphone-based self-tracking literature. Our review suggests that most of the smartphone-based self-tracking literature is concentrated in the first two quadrants of the conceptual framework: they tend to use objectively collected measurements (e.g., using mobile sensing) to deploy interventions aimed towards influencing mental or physical outcomes of interest. However, research in the other two quadrants was relatively sparse: fewer studies attempted to collect subjective measurements of physical and mental states to assess or influence physical outcomes of interest. Thus, future research should focus on filling in this gap in the literature by evaluating personal informatics systems that collect mental state information using subjective measures and quantify behavior change in relation to changing physical and mental states resulting from the intervention. There is especially a need to develop passive mobile sensing systems that can collect mood-related information unobtrusively from users (e.g., LiKamWa et al. 2013). The growth of mobile sensing systems in the physical domain has been rapid, and there is immense potential for this growth to percolate into the surrounding conceptual quadrants—namely to the subjective measurement-mental outcome of interest and subjective measurement—physical outcome of interest quadrants

Generally, research has prioritized certain components of personal informatics systems over others. For instance, some researchers focused on developing accurate sensing technologies in favor of administering user feedback, while other researchers were entirely focused on exploring optimal ways of generating actionable feedback for the user. Our results indicated that personal informatics work is currently dominated by computer science researchers, indicating a timely opportunity for behavioral researchers to get into the fray. Furthermore, we found limited theoretical integration in most of the extant literature, with findings indicating a shift in behavioral trajectories typically being considered in relation to one or two behavior change theories disciplinary-specific theories. While the use of classical theories in designing personal informatics is valuable, future work needs to further deploy theories developed specifically for the use of personal informatics systems (e.g., Li et al. 2010) in order to directly address the needs and habits of personal informatics application users. Such a consistency in theoretical integration will also ease cross-domain comparisons of the effectiveness of different personal informatics apps in inducing self-awareness and causing behavior change. Future theoretical work should integrate theories of personal informatics (e.g., Kersten-van Dijk et al. 2017) with behavior change theories (e.g., Prochaska and Velicer 1997), in order to develop a cross-disciplinary theoretical framework for designing optimal personal informatics applications.

6.4 Future Directions

The vast majority of reviewed papers in this literature review originated from the ACM database, suggesting that our results are skewed towards research produced by computer science and technically-oriented researchers. Furthermore, we found that an appreciation for individual differences in demographic and personality traits was generally absent from the reviewed empirical work, presumably because these were not variables of interest to technical researchers (e.g., Götz et al. 2017). In order to sustain behavior change interventions using digital self-tracking data, future work should identify how variations in individual differences are related to patterns of behavior change resulting from digitally engineered interventions. Indeed, there is a need for more work in the domain of understanding how an individual's personality and demographic traits relate to their motivations to self-track, and how these then influence the sustainability of the resulting behavior change.

An increase in cross-disciplinary dialogue between technologists and social scientists may facilitate an appreciation for individual differences in psychosocial characteristics (e.g., demographics, personality traits) during the design, implementation, and evaluation of smartphone-based self-tracking systems. Such interdisciplinary efforts are underway in the form of workshops (e.g., Campbell and Lane 2013), conferences (e.g., Rentfrow and Gosling 2012), and research initiatives (e.g., Life Sensing Consortium; lifesensingconsortium.org) that bring mobile sensing researchers from diverse disciplines into conversation with one other. An increase in interdisciplinary collaboration and widespread adoption of personal informatics models are likely to engender the next generation of personal informatics tools that customize their feedback to an individuals' psychological characteristics. We believe that customizing interventions according to individual differences will play an important role in facilitating self-reflection and sustained behavior change for the next generation of personal informatics systems.

It is encouraging to see that there are abundant deployment studies of different types of personal informatics studies in the literature. The diversity of applications of personal informatics system is particularly impressive, as is the commitment of researchers to pilot their proposed systems with real participants. While results pertaining to induced behavioral change vary across studies, we generally find that participants respond favorably to interventions and report increased feelings of self-awareness as a result. This work suggests that the future for personal informatics is bright, as more and more individuals are likely to adopt self-tracking methods as wearables and sensor-laden smartphones penetrate further into the human population. Future work should especially build upon two domains that contained sparse sensing literature: productivity and digital media use. Developing personal informatics systems for productivity tracking can assist organizations in monitoring employee productivity by displaying the times and locations at which an employee is at their most productive, and can further assist employees in maintaining adequate work-life balance by allowing employees to set time-based goals for work and recreational activities (see Mashhadi et al. 2016 for review). Similarly, sensing tools to examine detailed patterns of engagement with digital media can help curb concerns of social media abuse and its resulting detriments on mental health by prompting users to limit their time on the internet if it exceeds some predetermined threshold (i.e. Pardes 2019). More sophisticated applications could sense different kinds of social media use (i.e., active vs. passive use; Gerson et al. 2017) and alert users when they are engaged in types of social media usage that are typically associated with declines in mental well-being.

Moreover, future research should focus on deploying sensing work in non-Western settings. Virtually every cited study in this paper sampled from predominantly Western populations, as has been the tradition in behavioral science (Henrich et al. 2010). However, there are several Eastern social media platforms that rival the size and reach of their Western counterparts, such as WeChat (Lien and Cao 2014, Montag et al. 2018) and Weibo (Sullivan 2014). Similarly, over the last few years, the Quantified Self movement has diffused from the western hemisphere to the eastern hemisphere, especially to China (Yangjingjing 2012). The potential for personal informatics to succeed in the developing world is also bolstered by increasing smartphone penetration rates in fast-growing democratic nations such as India (Singh 2012). Hence, the spread of personal informatics around the world, coupled by the growth of non-Western social media platforms makes it essential for future research to focus on non-Western, multicultural samples in designing and deploying smartphone-based personal informatics systems. By deploying digital self-tracking platforms in developing countries around the world, we can accomplish two interrelated goals: (a) we can make digitized self-tracking a tool used at large by diverse individuals and (b) we can use the generated data to examine how richness in individual differences guides human-computer interaction. We look forward to social scientists and technologists collectively embracing the potential of self-tracking technologies in conducting interdisciplinary research.

Acknowledgements We thank Leela Srinivasan for assistance with the literature review and helpful feedback on earlier versions of the work presented in this manuscript.

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Chapter 7
Digital Brain Biomarkers of Human Cognition and Mood

Paul Dagum

Abstract By comparison to the functional metrics available in other medical disciplines, conventional measures of neuropsychiatric and neurodegenerative disorders have several limitations. They are obtrusive, requiring a subject to break from their normal routine. They are episodic and provide sparse snapshots of a patient only at the time of the assessment. They require subjects to perform a task outside of the context of everyday behavior. And lastly, they are poorly scalable, taxing limited resources. We present validation studies that demonstrate the clinical efficacy of a new approach in reproducing gold-standard neuropsychological measures. We discuss the neuroscience constructs and mathematical underpinnings of cognition and mood measurement from human-computer interaction data. We conclude with a discussion on four areas that we predict will be impacted by these new clinical measurements: (i) understanding of the interdependency between cognition and mood; (ii) nosology of psychiatric illnesses; (iii) drug discovery; and (iv) delivery of healthcare services.

7.1 Introduction

The twentieth century introduced electroencephalography, magnetic resonance imaging, genome sequencing and other novel techniques that advanced our understanding of neuroscience. But despite these advances, our progress in treating brain illnesses has been slow. We have struggled to translate discoveries into insights of psychopathology that improve functional outcomes. This struggle is rooted in how we measure brain function and how we diagnose. These measures whether for disorders of cognition or mood share several limitations.

The laboratory nature of existing clinical instruments are not objective measures of functional performance in the real world. This limits their utility in correlating the effect of exogenous and endogenous factors such as duress, lifestyle, illness, and drugs with symptom burden. A similar limitation existed in other disciplines such as

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_7

cardiology, where for example a normal resting electrocardiogram revealed nothing about a person's ability to climb a flight of stairs. Similar to a stress electrocardiogram, we need to measure a person's ecological resilience in their natural environment. But unlike a stress electrocardiogram, ecological brain measurements need to be unobtrusive and continuous.

Our measurements today are not ecological. They are obtrusive, requiring a subject to break from their normal routine. They are episodic and provide sparse snapshots of a patient only at the time of the assessment. They require subjects to perform a task outside of the context of everyday behavior. And lastly, they are poorly scalable, taxing limited resources.

Ecological measurement of brain function was unthinkable even a decade ago. But the emergence of ubiquitous mobile digital devices created the opportunity to passively and continuously collect digital signals from individuals. Early applications of these digital signals included cybersecurity where they were used to create digital fingerprints of cybercriminals (Dagum 2018a).

In 2013, following our early work in cybersecurity, we launched several clinical studies that were the first to demonstrate the feasibility of creating digital biomarkers that correlate with laboratory assessments of mood and cognition using passively acquired data from the daily use of a smartphone (Kerchner et al. 2015; Dagum 2018b). These digital biomarkers meet our ecological requirements of providing insight into day-to-day functional performance. They are unobtrusive, placing no burden on the subject beyond the normal use of a smartphone. They provide dense daily assessments with potential insight into hourly or daily variations in brain function. They scale globally to over two billion smartphone users today (Statistica 2019).

In the real-world, brain function is affected by illness and environment influences such as drugs and insomnia, and performance will vary from what we measure in a laboratory setting. We postulate that the daily variability in the digital biomarkers will provide rich temporal insight into state-dependent signatures of cognition and emotional health that may be predictive of disease and environmental effects. These biomarker signatures (Montag 2021; Montag 2023) define digital phenotypes (Insel 2017) that similar to cardiac phenotypes may have distinct clinical profiles and outcomes. This has the potential to create the foundation of a new nosology of mental illness.

7.2 Human-Computer Interactions

The interface between humans and computers has evolved over the past seven decades and continues to evolve. Interfaces today range from ubiquitous touch-screens found in smartphones and automobile dashboards, to mixed-reality interfaces in smart-glasses, and to voice user interfaces (VUI). We have recently witnessed the emergence of direct brain-computer interfaces (BCI) that may someday replace human-computer interfaces (HCI).

Regardless of the interface, whether it is today's HCI or tomorrow's BCI, we can decompose the interaction model into three fundamental components. The first component is *information presentation* by the computer. This information presentation is broad and often domain and modality specific. Visual examples predominate and include a scrollable list of selectable items, keyboard input, navigation map, or performance indicators. Examples of auditory presentation are fewer, analog, carry lower information capacity and include voice responses in VUI systems.

The second component is *mental processing* by the human of the information presented. Mental processing relies on the integrity of neural circuits. The cognitive constructs needed for mental processing depend on the nature of the information presented and what is expected of the human. These constructs range from attention (selective, sustained), memory (working, visual, delayed), speed of information processing, to verbal fluency and executive function.

The third component is the *human response* that follows the mental processing step. Both the type of response and the time to respond to the presented information are measurable by the interface. The total response time from presentation includes the motor response time. By comparison to mental processing time, that exhibits significant variability, long duration and high correlation with total response time, the motor response time shows low variability, shorter duration and poor correlation (Botwinick and Thompson 1966). Figure 7.1 illustrates the three components of the human-computer interaction model.

The speed at which different types of information is processed by humans varies across a population and modality of presentation. For a specific modality, the population variation captures normal variation linked to a general factor of intelligence and differences in mental processing that include the effect of injuries and illnesses. This has been confirmed by a century of traditional neurocognitive testing from paper and pencil tests, to computer tests, to auditory tests (Strauss et al. 2006). These tests involve completing repeated simple primitive tasks that are scored on completion time. Like HCI models, these gold-standard tests can be decomposed into information presentation, mental processing and human response.

Ecological measurement moves us beyond a population distribution of functional capacity to individual longitudinal measures of functional performance. Moment-to-moment functional performance is affected by ecological causes that are measurable from human-computer interactions as delays or errors in the human response component of an individual. Common ecological causes include fatigue, mood disorders, and chronic medical illnesses that affect brain function whether from poorly regulated blood glucose (e.g., diabetes mellitus), acid-base imbalance (e.g., chronic-obstructive pulmonary disease), or inadequate cerebral perfusion (e.g., ischemic heart disease). Monitoring ecological biomarkers together with behavior observed through passive capture of phone behavioral data (Markowetz et al. 2014) or self-journaling (Kubiak and Smyth 2019) may help bridge our current behavioral nosology of mental illness with proximal digital measures of central nervous system function.

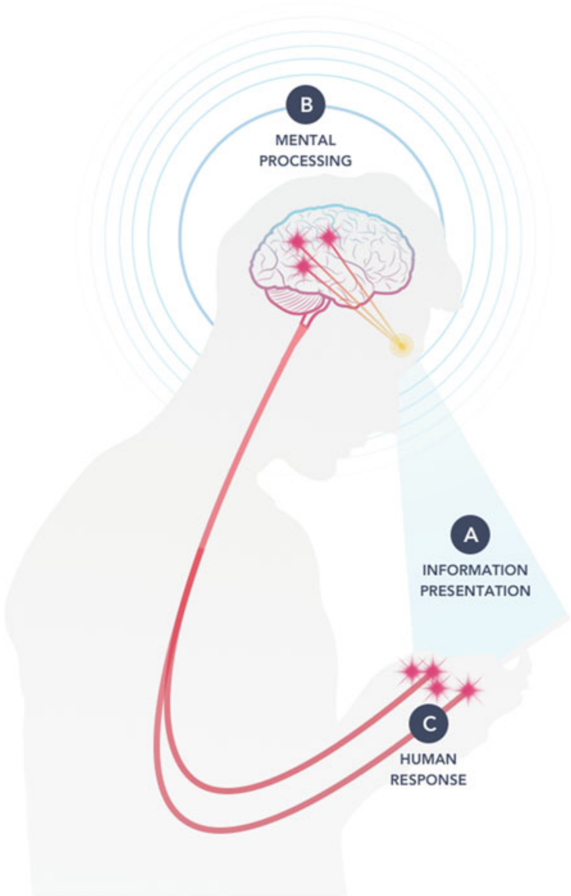


Fig. 7.1 An illustration of **a** information presentation, **b** mental processing and **c** human response that comprise the fundamental components of human-computer interaction. The type of information presentation, for example a choice selection, and the response time when measured repeatedly by the day-to-day use of a smartphone provide passive, ecological, in-the-moment insight into a user's cognitive and emotional state. Standard neuropsychological instruments of cognition and mood lie in low-dimensional submanifolds of the high-dimensional space formed by the different types of information presentation stimuli and features

7.3 Digital Biomarkers of Cognition

In January of 2014, we launched a study to demonstrate the feasibility of decoding human-computer interactions into clinical measures of neuropsychological function. We recruited 27 subjects (ages 18–34 years, education 14.1 $\pm$ 2.3 years, M:F 8:19) volunteered for neuropsychological assessment and installed an app on their smartphone that passively captured their HCI from touchscreen activity. All participants, recruited via social media, signed an informed consent form. Inclusion criteria required participants to be functional English speaking and active users of a smartphone. The protocol involved 3 h of psychometric assessment followed by installation of an app on their smartphone. The test battery is shown in the first column of Table 7.1. A single psychometrician performed all testing in a standard assessment clinic. The app on the phone ran passively in the background and captured patterns

Table 7.1 Fourteen neurocognitive assessments covering five cognitive domains and dexterity were performed by a neuropsychologist

Cognitive predictions			
	Mean (SD)	Range	R (predicted), p-value
Working memory			
Digits forward	10.9 (2.7)	7–15	0.71 ± 0.10, 10^{-4}
Digits backward	8.3 (2.7)	4–14	0.75 ± 0.08, 10^{-5}
Executive function			
Trail A	23.0 (7.6)	12–39	0.70 ± 0.10, 10^{-4}
Trail B	53.3 (13.1)	37–88	0.82 ± 0.06, 10^{-6}
Symbol digit modality	55.8 (7.7)	43–67	0.70 ± 0.10, 10^{-4}
Language			
Animal fluency	22.5 (3.8)	15–30	0.67 ± 0.11, 10^{-4}
FAS phonemic fluency	42 (7.1)	27–52	0.63 ± 0.12, 10^{-3}
Dexterity			
Grooved pegboard test (dominant hand)	62.7 (6.7)	51–75	0.73 ± 0.09, 10^{-4}
Memory			
California verbal learning test (delayed free recall)	14.1 (1.9)	9–16	0.62 ± 0.12, 10^{-3}
WMS-III logical memory (delayed free recall)	29.4 (6.2)	18–42	0.81 ± 0.07, 10^{-6}
Brief visuospatial memory test (delayed free recall)	10.2 (1.8)	5–12	0.77 ± 0.08, 10^{-5}
Intelligence scale			
WAIS-IV block design	46.1 (12.8)	12–61	0.83 ± 0.06, 10^{-6}
WAIS-IV matrix reasoning	22.1 (3.3)	12–26	0.80 ± 0.07, 10^{-6}
WAIS-IV vocabulary	40.6 (4.0)	31–50	0.67 ± 0.11, 10^{-4}

Shown are the group mean and standard deviation, range of score, and the correlation between each test and the cross-validated prediction constructed from the digital biomarkers for that test

and timings of touch-screen user activity that included swipes, taps, and keystroke events, comprising the human-computer interactions.

From the HCI events we identified 45 interaction patterns using high-dimensionality reduction. Each pattern represents a task that is repeated up to several hundred times per day by a user during normal use of their phone. Most patterns consisted of two successive events, such as tapping on the space-bar followed by the first character of a word, or tapping the “delete” key followed by another “delete” key tap. Some patterns were collected in a specific context of use. For example, tapping on a character followed by another character could be collected at the beginning of a word, middle of a word, or end of a word. Each pattern generated a time-series composed of the time interval between patterns. The time-series were segmented into daily time-series. To each daily time-series we applied 23 mathematical transforms to produce 1,035 distinct daily features that we term *digital biomarkers.*

For each participant we selected the first 7 days of data following their test date. A biomarker was considered a candidate for a neurocognitive test if over the 7 day window the 7 correlations between sorted biomarker values and the test scores were stable (meaning of the same sign). The 2-dimensional design matrix for the supervised kernel principal component analysis (PCA) was constructed by selecting the peak value of each candidate biomarker over the 7 days. For each test, we constructed a linear reproducing Hilbert space kernel from the biomarkers and used a supervised kernel principal component analysis (Dagum 2018b) with leave-one-out-cross-validation (LOOCV) as follows. To predict the 1st participant test result the model fitting algorithm was run on the remaining participants without access to the 1st participant's data, and so forth iterating 27 times to generate the 27 predictions. Cross-validation allows us to control the risk of over-fitting the data because each participant's data is never used in fitting the model used to predict that participant's results.

These preliminary results suggested that passive HCI measures from smartphone use could be a continuous ecological surrogate for laboratory-based neuropsychological assessment. Smartphone human-computer interaction data from the 7 days following the neuropsychological assessment showed a range of correlations from 0.62 to 0.83 with the neurocognitive test scores. Table 7.1 shows the correlation between each neurocognitive test and the cross-validated predictions of the supervised kernel PCA constructed from the biomarkers for that test. Figure 7.2 shows each participant test score and the digital biomarker prediction for (a) digits backward, (b) symbol digit modality, (c) animal fluency, (d) Wechsler Memory Scale-3rd Edition (WMS-III) logical memory (delayed free recall), (e) brief visuospatial memory test (delayed free recall), and (f) Wechsler Adult Intelligence Scale-4th Edition (WAIS-IV) block.

An obvious limitation of this study was the small size ($n = 27$) relative to the large number of potential biomarkers ($n = 1{,}035$). To counter the risk of over-fitting these results, predictions were made using LOOCV, stringent confidence level ($p < 10^{-4}$) and a simple linear kernel that was regularized. A further limitation was that the neuropsychological assessment occurred at one time point and the digital features were collected ecologically over the first 7 days following the assessment. For clinical assessments, we have found that the real-world, continuous assessment yields critical information relevant to function.

7.4 Digital Biomarkers of Mood

A core feature of major depressive disorder (MDD) is anhedonia defined as a diminished interest to previously rewarding stimuli. Anhedonia is present in approximate 40% of patients with MDD and may represent a physiologically distinct sub-group of patients with motivational and reward processing deficits (Keedwell et al. 2005). To identify digital biomarkers associated with depression and anhedonia we analyzed

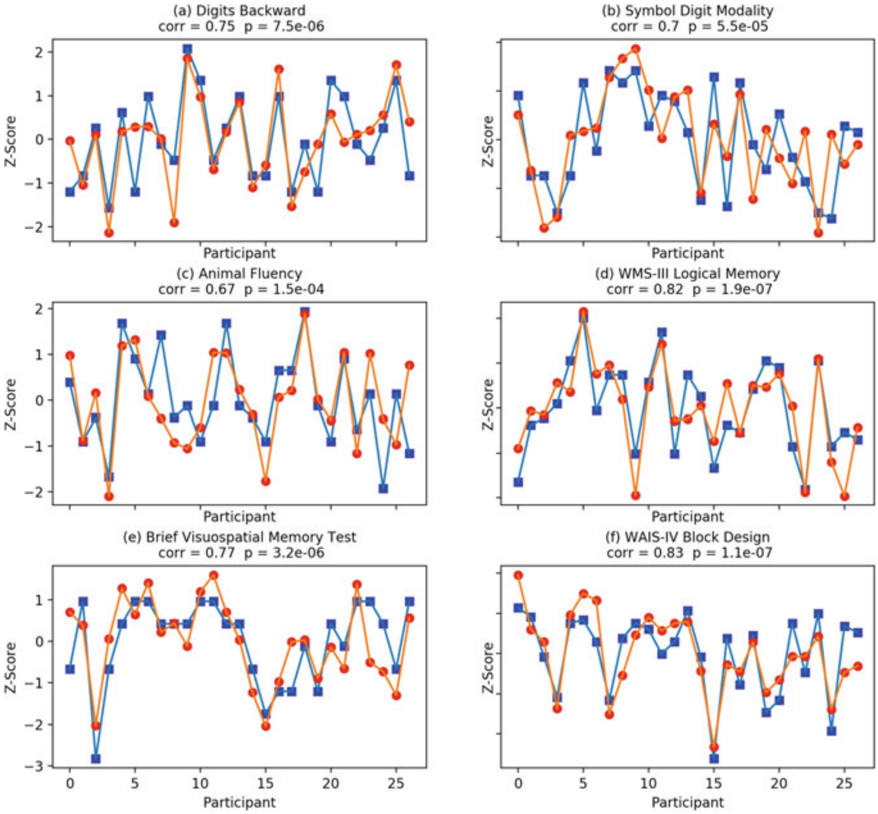


Fig. 7.2 A blue square represents a participant test Z-score normed to the 27 participant scores and a red circle represents the digital biomarker prediction Z-score normed to the 27 predictions. Test scores and predictions shown are **a** digits backward, **b** symbol digit modality, **c** animal fluency, **d** Wechsler memory Scale-3rd Edition (WMS-III) logical memory (delayed free recall), **e** brief visuospatial memory test (delayed free recall), and **f** Wechsler adult intelligence scale-4th Edition (WAIS-IV) block design

human-computer interaction from the smartphone of subjects enrolled in a multi-center, double blind-clinical trial for the treatment of MDD (Madrid et al. 2017; Smith et al. 2018). Of the 15 subjects randomized (ages 18–48 years, M:F 3:12) 10 were Caucasians, 4 were African-Americans and 1 was Asian, 2 were Hispanic and 13 were not Hispanic.

We used 7 days of smartphone data collected in the first week following baseline assessment. Baseline assessment included the Montgomery-Asberg Depression Rating Scale (MADRS) and Snaith Hamilton Pleasure Scale (SHAPS) for anhedonia. We used the same panel of 1,035 daily digital biomarkers generated from the touch-screen human-computer interactions of each subject. We again used a supervised kernel PCA with a 2-dimensional design matrix similarly constructed by selecting the peak value of each candidate biomarker over the 7 days. For each test, we constructed a linear reproducing Hilbert space kernel from the biomarkers and used a supervised kernel principal component analysis with LOOCV. The correlation between the MADRS and SHAPS assessment of depression and anhedonia and the cross-validated predictions of the supervised kernel PCA constructed from the biomarkers for that assessment where Spearman $r = 0.67$, $p = 0.024$ and Spearman $r = 0.82$, $p = 0.001$ respectively.

In another research study from 2017 to 2018 (ClinicalTrials.gov 2017), we demonstrated that digital brain biomarkers are sensitive and specific to temporal changes in mood and clinical severity. Ten participants (ages 44 ± 10 years, education 15 ± 1 years, M:F 5:5) were enrolled from a private outpatient psychiatric clinic with a diagnosis of either Major Depressive Disorder (MDD) or Bipolar Depression (BD) confirmed using the Structured Clinical Interview for DSM Disorders-Clinical Trials (SCID-CT). Participants consented to repeat weekly clinical assessment for eight months and to installing the smartphone app on their smartphone during this entire period. All clinical assessments were performed by the same person.

For each participant, we used the HCI data collected on the day of the clinical assessment to create the digital biomarkers. This differs from our prior studies where we used data collected over a 7-day period to select the digital biomarkers. We treated the repeated clinical assessments as independent measures and used an extension of supervised kernel PCA (Barshan et al. 2011) to longitudinal data (Staples et al. 2018). The 2-dimensional design matrix of the supervised longitudinal kernel PCA for a target clinical assessment was constructed using digital biomarkers selected from the full panel only if they satisfied a false-discovery rate (FDR) of 5% and 0.5% for mood and clinical severity, respectively, using the Benjamini-Hochberg procedure (Benjamini and Hochberg 1995). As an additional FDR control, we computed the permutation p-value of the results using 100 random permutations of the training targets (Winkler et al. 2014). Using an FDR of 5% to select the digital biomarkers used in the model for a neuropsychological test guarantees that at most 1 in 20 selected biomarkers is a false positive.

The output of the supervised longitudinal kernel PCA was evaluated using both leave-one-out cross-validation (LOOCV) and out-of-bag prediction error using bootstrap aggregation. The supervised longitudinal kernel PCA treated repeated samples as independent in the model, required for the validity of cross validation at the patient-test level in this longitudinal study (Bergmeir et al. 2018). Because of the small sample size, we further performed permutation testing to validate the results. These tests confirmed invariance of the LOOCV results following permutation of the participant's repeated clinical assessments as would be expected if the repeated samples were truly independent in the model. In contrast, re-fitting the cross-validated models following permutation of the targets between participants, that is between participant's test scores, led to no statistically significant predictions. This last permutation test would yield statistically significant results if the model-fitting procedure was over-fitting the data.

To assess mood we used the Patient Health Questionnaire 9 (PHQ-9) scale modified by asking participants to respond from their experience over the past 24 h only.

Clinical severity was assessed using the Clinical Global Impression—Severity (CGI-S). Table 7.2 shows the correlation between each of the two assessments and the cross-validated predictions from the supervised longitudinal kernel. Figure 7.3 shows each participant assessments and the digital biomarker predictions for (a) PHQ-9 24 h and (b) CGI-S.

The results from both these studies demonstrate that the panel of digital biomarkers constructed from passively acquired human-computer interactions could be a continuous ecological surrogate for laboratory-based assessments for mood disorders and

Table 7.2 Subjects were instructed to complete the Patient Health Questionaire-9 based on their assessment over the past 24 h only

Mood predictions		
	Patient Health Questionaire-9 (24 h)	Clinical Global Impression—Severity
Mean (SD)	13.3 (6.1)	4.0 (1.4)
Range	0–26	2–6
Observations	170	128
R (predicted), p-value	0.63, 2.8e–20	0.71, 7.0e–21

Clinical severity was scored by a single clinician using the Clinical Global Impression for Severity scale. Shown are the group mean and standard deviation, range of score, total number of observations, the correlation and correlation p-value between the instrument and the cross-validated prediction constructed from the digital biomarkers

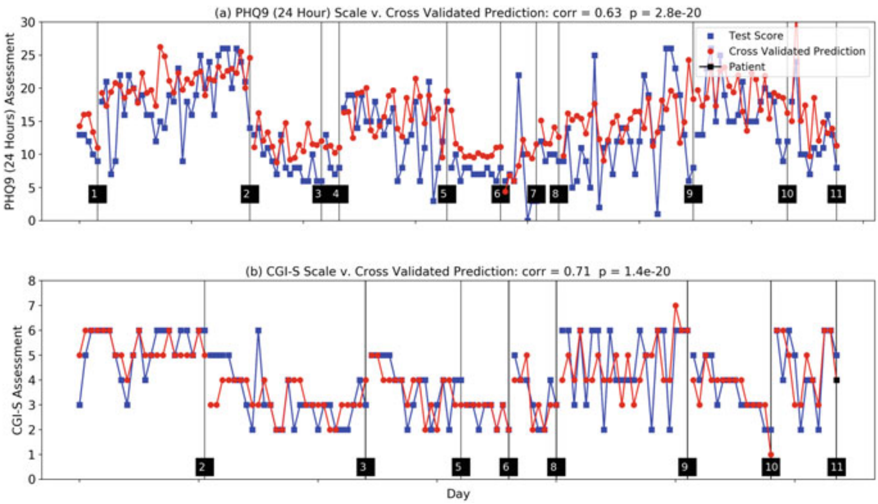


Fig. 7.3 A blue square represents a participant assessment score and a red circle represents the digital biomarker prediction. Assessment scores and predictions shown are **a** patient health questionnaire 9 using a 24-h recall (PHQ 9 24 h) and **b** clinical global impression scale for severity (CGI-S)

of clinical severity. These studies demonstrated feasibility and early clinical validity of our approach. The risk of over-fitting the data and multiple comparisons was controlled using strict false-discovery rates and permutation testing.

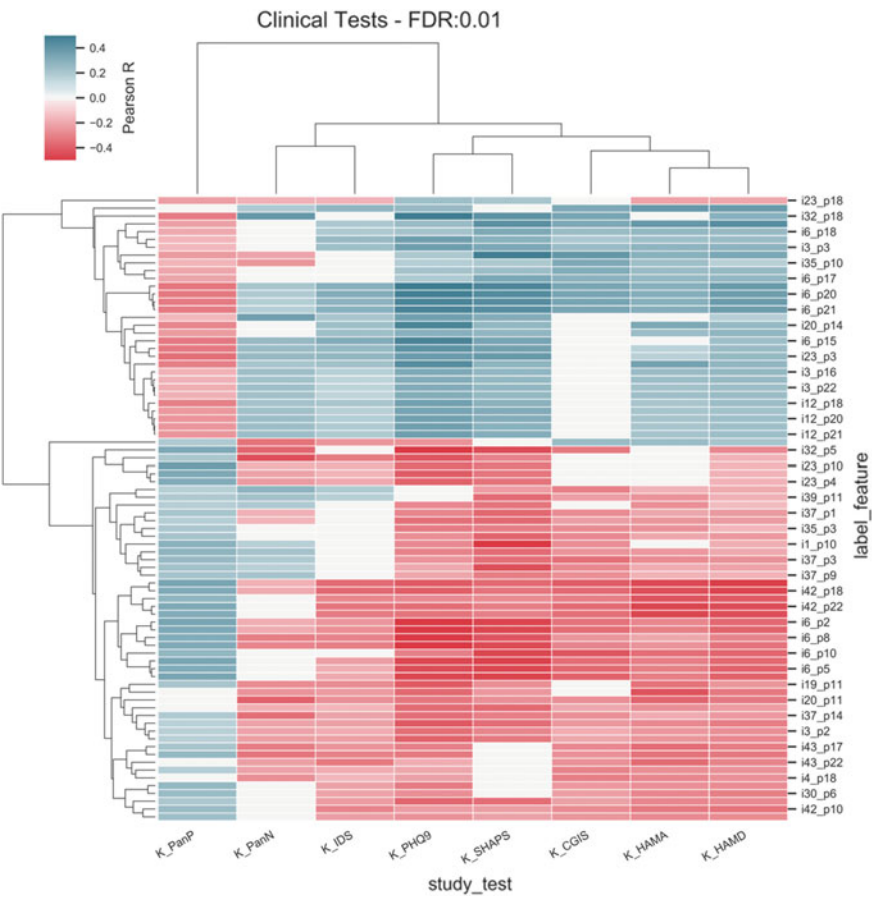
We have shown through these studies that standard cognitive and mood assessments performed by a neuropsychologist lie in a high-dimensional space of 1,035 digital biomarkers generated from touchscreen HCI patterns. Reconstructing an assessment reduces to identifying the minimal set of biomarkers that spans a low-dimensional submanifold containing the assessment. To visualize this biomarker space against the many cognitive and mood assessments, Figs. 7.4 and 7.5 show a heatmap of the correlations between specific digital biomarkers and target measures. For all correlations, p-values were corrected to limit the false discovery rate to 1 in 100. Correlations with a p-value below this threshold are shown in gray, and any biomarkers that did not exceed this threshold on at least one target measure are not shown. Rows and columns are sorted using hierarchical clustering so rows and columns that are more similar are positioned closer in the plot and have a shorter dendrogram line.

7.5 Future Directions

Nobel laurate Sydney Brenner has said that "progress in science depends on new techniques, new discoveries and new ideas, probably in that order". We have introduced a new paradigm for measuring cognition and mood that is based on ubiquitous human-computer interactions from smartphone use. With the ubiquitous use of smartphones (Andone et al. 2016), we anticipate that this paradigm may have profound implications in our understanding of brain disorders, functional outcomes, and lead to new therapeutic discoveries. We specifically discuss four areas that could be impacted: (i) understanding of the interdependency between cognition and mood; (ii) nosology of psychiatric illnesses; (iii) drug discovery; and (iv) delivery of healthcare services.

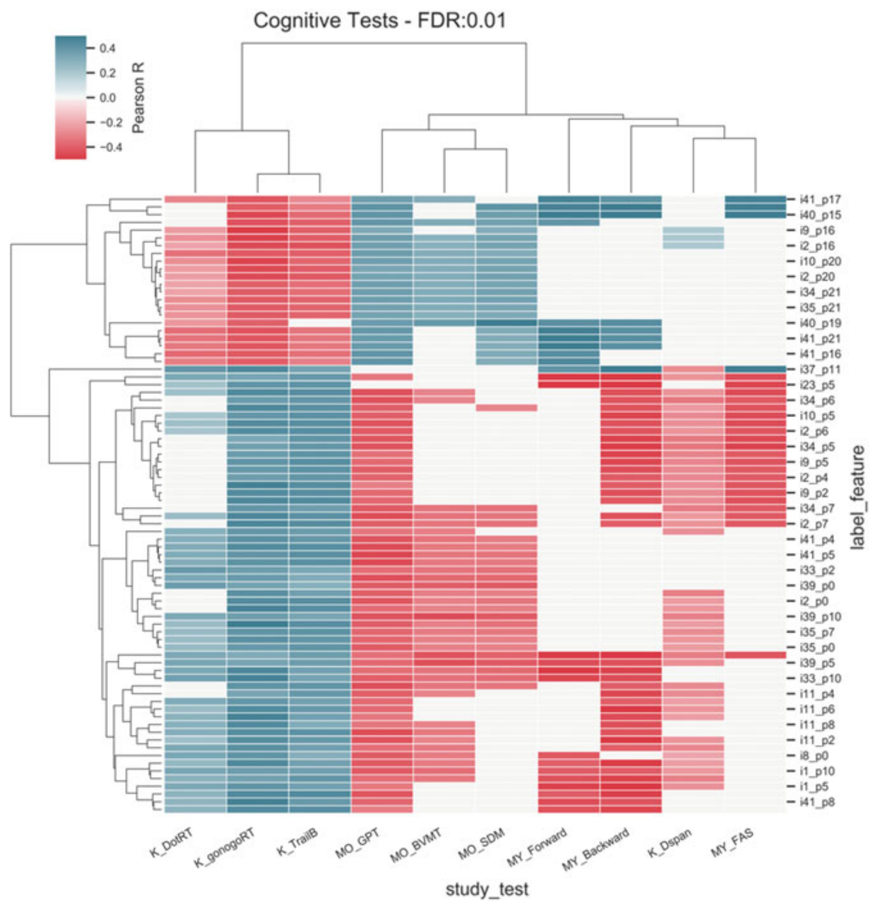
Mental disorders that include mood and psychosis show remitting and relapsing behavior that can be exacerbated by triggers or improved with therapy. The potential for rapid clinical fluctuations in these disorders can have profound effects on brain function. These state-dependent changes in cognition are often more disabling than the affective symptoms. Our understanding of this interdependency has been hampered by episodic clinic measurements of cognition that seek to measure trait level functional capacity in the laboratory. The ability to measure both mood and cognition ecologically and continuously could improve our understanding of how mood regulates cognition and cognition regulates mood. This could lead to new therapies and improved function.

Diagnosis of mental disorders today involves a constellation of clinical symptoms that define a human behavioral phenotype. There has been significant effort over the past decade to create a new nosology of mental disease, one that is based on clinical measurements that are proximal to the psychopathology. Mental illness is syndromal and identification of biological substrates of disease risk and burden would enable



Clinical Tests		
Abbreviation	***Test***	***Construct***
PAN_P	PANAS Positive	Positive Affect
PAN_N	PANAS Negative	Negative Affect
IDS	Depression Scale	Depression
PHQ 9	Patient Health Questionnaire	Depression
SHAPS	Snaith-Hamilton Pleasure Scale	Anhedonia
CGIS	Clinician Global Impression- Severity	Global psychiatric functioning
HAMA	Hamilton Anxiety Scale	Anxiety
HAMD	Hamilton Depression Scale	Depression

Fig. 7.4 Correlations between the top Biomarkers and Clinical measures. The p-values from all correlations are corrected to limit the false discovery rate to 1%. Correlations with a p-value below this threshold are shown in gray



Cognitive Tasks		
Abbreviation	***Test***	***Construct***
DotRT	Choice reaction time	Attention and Motor Speed
gonogoRT	Go/no-go reaction time (RT)	Attention and Behavioral Inhibition
TrailB	Trail Making Task B	Executive Function
GPT	Grooved Pegboard Task	Visuomotor Coordination
BVMT	Brief Visuospatial Memory Test	Visuospatial Memory
SDM	Symbol Digit Modalities Test	Executive Functioning
Forward	Digit Span Forward	Working Memory
Backward	Digit Span Backward	Executive Functioning
Dspan	Digit Span Visual	Working Memory
FAS	F-A-S fluency task	Phonemic Verbal Fluency

Fig. 7.5 Correlations between the top Biomarkers and Cognitive tasks. (Details are the same as for Fig. 7.3)

significant progress. Digital biomarkers of mood and cognition, with their ecological and continuous measurement, may be the right clinical constructs to correlate with mental illness morbidity.

Drug development for mental and neurological diseases costs far more than other medications to develop and is least likely to receive U.S. Food and Drug Administration approval. Common strategies for reducing clinical trial duration and cost include patient stratification, study enrichment, and early endpoint detection. But all these strategies require sensitive and specific measures of disease pathology which have been hard to create for most brain disorders. This is compounded further by the recognition that our inadequate understanding of disease etiology, onset, progression, treatment and outcome has limited drug development to drugs that address symptoms, not pathology.

Pharmaceutical companies have been quick to embrace the promise of digital biomarkers of mood and cognition in drug development (Business Wire 2017; PR Newswire 2018). With completion of active phase II clinical trials, we will have a clearer picture of the extent to which these digital biomarkers can contribute to a new generation of drugs that are safer, more efficacious, phenotype-focused therapeutic agents. Digital biomarkers create the possibility of companion diagnostics and targeted therapeutics that are more closely tailored to specific patient populations.

The measurement challenge in psychiatry has contributed significantly to the cost of care and poor outcomes of mental illnesses. Even with existing therapies, medication adherence is poor and treatment effectiveness inadequate because of therapeutic inertia or lack of symptom reporting by patients. Using these ecological digital biomarkers in outpatient telehealth to quantify disease activity, trigger treatment review and determine the need for early intervention. Provides a novel opportunity to reshape the brick-and-mortar care model of chronic disease into one that is ecological to the patient, measurement based, and can preempt disease progression.

We conclude with our views on privacy. Healthcare delivery in the United States is a highly regulated industry. Patients must consent to receive care and providers must comply with the Health Insurance Portability and Accountability Act (HIPAA) of 1996 that legislates provisions for data privacy and security to safeguard medical information. Digital brain biomarkers and digital phenotypes are not an exception. These are clinical measures of cognitive and emotional state with the potential to predict a person's behavior and response to illness, therapy and societal challenges. They represent medical tests that should be taken exclusively under a patient-provider consent-to-care relationship, governed by HIPAA privacy and security policies and used in the context of early intervention and therapeutic decision support by providers.

Conflict of Interest Paul Dagum is the founder of Mindstrong Health, a company developing digital phenotyping products for mental healthcare delivery. He served as its Chief Executive Officer from its founding in 2013 through October 2019 and was granted five U.S. patents on digital phenotyping and digital biomarkers. Dagum is currently co-founder and CEO of Applied Cognition developing diagnostic and therapeutic solutions for Alzheimer's disease. Dagum owns stock in Mindstrong Health and in Applied Cognition.

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Chapter 8
Mining Facebook Data for Personality Prediction: An Overview

Davide Marengo and Michele Settanni

Abstract Users' interaction with Facebook generates trails of digital footprints, consisting of activity logs, "Likes", and textual and visual data posted by users, which are extensively collected and mined for commercial purposes, and represent a precious data source for researchers. Recent studies have demonstrated that features obtained using these data show significant links with users' demographic, behavioral, and psychosocial characteristics. The existence of these links can be exploited for the development of predictive models allowing for the unobtrusive identification of online users' characteristics based on their recorded online behaviors. Here, we review the literature exploring use of different forms of digital footprints collected on Facebook, the most used social media platform, for the prediction of personality traits. Then, based on selected studies, meta-analytic calculations are performed to establish the overall accuracy of predictions based on the analyses of digital footprints collected on Facebook. Overall, the accuracy of personality predictions based on the mining of digital footprints extracted from Facebook appear to be moderate, and similar to that achievable using data collected on other social media platforms.

8.1 Introduction

Since its creation in 2004, Facebook has experienced a steady increase in active users, reaching a total of 2.41 billion monthly active users as of the second quarter of 2019 (Statista 2019). In spite of growing competition by other social media platforms—such as Instagram (which is also currently owned by Facebook), Twitter, and Snapchat—and mounting controversies concerning the handling of user privacy (e.g., see the recent Cambridge Analytica scandal, Cadwalladr and Graham-Harrison 2018), as of 2019, Facebook remains the most used social media platform worldwide. Every day, millions of Internet users from different cultural contexts express their thoughts, emotions, and beliefs by writing, posting, and sharing content on Facebook,

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_8

which can be commented and/or endorsed ("liked" in the Facebook jargon) by their network of Facebook friends, or the overall Facebook community if the user profile is public. This unceasing interactive process produces a massive dataset of user-generated data, also referred to as "digital footprints", "digital records", or "digital traces" (e.g., Settanni and Marengo 2015; Youyou et al. 2015; Farnadi et al. 2016) consisting of personal information, activity logs, texts, pictures, and videos, with potential connections to users' offline behavioral and psychosocial characteristics.

In the research area of psycho-informatics (Markowetz et al. 2014), an increasing number of studies have explored the feasibility of mining digital footprints from Facebook, as well as those collectable from other social media platforms, in efforts to infer individual psychosocial and behavioral characteristics, such as personality (e.g., Golbeck et al. 2011; Kosinski et al. 2013; Liu et al. 2016; Farnadi et al. 2016) psychological distress (e.g., Choudhury et al. 2013; Settanni and Marengo 2015); for an overview see Settanni et al. 2018) and engagement in offline risk behaviors (e.g., alcohol use, Curtis et al. 2018). One of the earliest and most enduring project in this field of study is the my Personality project (Kosinski et al. 2013), which has attracted over 6 million Facebook users who have donated their digital footprints and responded to online questionnaires on a wide variety of psychometric measures, including Big Five personality traits, satisfaction with life, and intelligence.

Studies in this field share a common research design, broadly consisting of four steps: (1) User digital footprints are collected and mined for the automated extraction of multiple features; (2) Information about user individual characteristics is collected by means of different approaches (e.g., online survey, ecological momentary assessment via mobile apps); (3) Datasets combining the features extracted from digital traces and users' information are mined to explore associations between features and users' characteristics, and to train models aimed at predicting individuals' traits, typically using a machine-learning approach; and (4) Competing trained models are compared based on their accuracy in predicting users' characteristics on new independent datasets, leading to the identification of the best performing model. Most of existing studies employing this approach have explored the feasibility of mining digital footprints for the prediction of personality traits, as defined by the Big Five model (McCrae and Costa 1987; McCrae and John 1992) and the Dark Triad model (Paulhus and Williams 2002). The focus on personality is largely due to the importance of personality in predicting many life-course aspects for individuals, including academic success (e.g., Komarraju et al. 2009), job performance (e.g., Neal et al. 2012), financial decision making (Lauriola and Levin 2001; Bibby and Ferguson 2011), health and health-related behaviors (e.g., Soldz and Vaillant 1999; Bogg and Roberts 2004, 2013), subjective well-being (e.g., Hayes and Joseph 2003), and online behaviors (e.g., Matz et al. 2017).

Due to the current dominant position of Facebook over all existing social media platforms, the majority of existing studies exploring digital footprints for the prediction of personality traits have focused on the use of Facebook data. In this chapter, we present an overview of these studies discussing differences in the types of examined digital footprints, and the various analytical approaches used for mining them. Next, we refer to existing meta-analytical results to discuss the accuracy of prediction based on digital footprints. Finally, we discuss ethical issues related to this field of study, in particular with respect to privacy violations. Popularity of social media platforms can drastically change over time, resulting in a significant decline in user activity (e.g., Myspace, Ribeiro and Faloutsos 2015), and eventually, this may apply to Facebook. Still, regardless of the social media platform under focus, current findings indicate the potential of the analysis of social media data for research in *psychoinformatics* is expected to increase in the future as technology improves, and new methodologies are developed for the analysis of digital footprints (Hinds and Joinson 2019).

8.2 Facebook Digital Footprints and Their Use for the Study of Personality

Facebook provides developers with access to the digital footprints of consenting Facebook users, which can be accessed via a specifically-devised application programming interface (API), the Facebook Graph API (Facebook for developers 2019a). Following the Cambridge Analytica scandal, Facebook has introduced stricter requirements for accessing user data (Facebook for developers 2019b). Starting from August 2018, in order to be granted extended login permissions (e.g., access to user posts, or Likes), Facebook requires all apps to undergo a review process requiring developers to explain in details how they plan to use and manage user data; further, developers are required to pass a business verification procedure, ultimately limiting data access to business companies. Non-business developers (e.g., researchers) can still access user data (excluding user posts) if they pass an individual verification procedure. Downloadable user data includes personal information (e.g., name, age, gender, hometown), as well as posts, likes, pictures, and videos shared by the users on their Facebook wall. Access to posts, likes, pictures, and videos, include the possibility to download the actual user-generated content, as well as attached metadata (e.g., day and time of posting, received likes and comments). In the following sections, we present a brief literature overview of the studies that analyzed the connection between different types of Facebook digital footprints and personality, and describe some of the approaches used to mine collected data for prediction purposes.

Demographics and activity statistics. Facebook provides researchers with a vast array of user demographic information, such as age, gender, geographical location, and information about activity on Facebook, such as number of friends, and frequency and time of online posting. Furthermore, based on the examination of users' feed data, it is possible to compute summary statistics of users' specific online behaviors, such as the number of times the user has updated his/her Facebook status, uploaded photos or videos, sent or accepted a friend request, the number of events he/she attended, or the number of times he/she has been tagged in a photo.

Studies have shown significant links between activity statistics and personality, and specifically, the Big 5 traits have been shown to be significantly associated with users' behaviors on social media. For example, individuals with high Extraversion have been characterized by higher levels of activity on social media, and have a greater number of friends (Kosinski et al. 2014) than introverted individuals. Individuals with high Conscientiousness appear to be cautious in managing their social media profiles; they post fewer pictures, and engage in less group activity on social media (Kosinski et al. 2014). Furthermore, individuals with high openness tend to have larger networks than individuals low on the trait (Quercia et al. 2012). Studies varies in the type of analyses employed to investigate the links between extracted features, and personality. Gosling and colleagues (2011) studied bivariate associations between count statistics of a wide range of user activity information, including the number of photos, number of wall posts, the total number of friends, and personality ratings provided by both the user itself and an external observer. Findings showed that both self-report and observer-rated Extraversion scores had positive associations with the number of user wall posts, uploaded photos, and the size of the friendship network, while self-report openness was positively related with the number of user online. In turn, Wald and colleagues (2012) extracted 31 features from users' profile information and wall post activity -including age, gender, relationship status, and the number of friends, photos, interests, and comments—to test them as attributes for personality prediction using a set of machine learning algorithms. When examining the predictive power of single features, number of friends emerged as the stronger predictor of individual differences in agreeableness. Trained machine-learning models combining all features showed good accuracy (75% of correctly classified individuals) in detecting individuals with high openness scores (over the 90th percentile), while prediction on other traits was less satisfactory (<0.65% of accuracy).

Facebook likes. Facebook gives its users the possibility to "like" Facebook pages created by groups, companies, public figures, or external websites. Likes represent a mechanism used by Facebook users to express their positive association with specific web pages, comments, photos, and offline activities among others (Youyou et al. 2015). By accessing user Likes data through the Graph API (*user_likes* authorization), the following information can be obtained: the name of each page liked by the user, the category each page was registered in by their creators (e.g., *musician/band*; *Media/News Company*; *Italian Restaurant*), and a timestamp indicating when each page was liked by the user.

Several links exist the frequency of "Like" behaviors and users' personality. For example, individuals scoring high on conscientiousness tend to express less "Likes" on Facebook (Kosinski et al. 2014), while individuals high on openness tend to "Like" more content found on social media (Bachrach et al. 2012). Likes can also be mined to obtain information about users' interests and preferences as regards brands, politics, music, etc. However, because of the massive number of existing Facebook pages (>42 million pages), when examined at the page-level, user Likes data usually generates very large sparse logical matrices (i.e., matrix in which each row represents a user and each column represents a specific page), even at small sample sizes. For this reason, examining user Likes data for personality prediction generally requires the implementation of some form of dimensionality reduction method on the predictors set (i.e., digital footprints, in this case Likes). For example, Kosinski and colleagues (2013) processed a large matrix consisting of an average of 170 liked pages per 58,466 Facebook users using singular value decomposition (SVD), retaining a smaller subset 100 SVD components for performing personality predictions using logistic regression. When applied to Facebook Likes, the emerging SVD components may be interpreted as reflecting latent users' interests and preferences emerging from the co-occurrence of Likes to similar pages, e.g., persons who "likes" the official Facebook page of Harry Potter and Lord of the Rings movies tend to score similarly on a SVD component reflecting an interest in fantasy novels or movies. Using this approach, Kosinski and colleagues found remarkable accuracy prediction; in particular concerning the 'Openness' trait, for which score predictions based on user's Likes was found to be roughly as informative as using self-report personality scores (Kosinski et al. 2013). Using SVD can improve performance albeit at the expense of the interpretability of results, since information about user specific preferences is lost in the process of producing SVD components, and interpretation of emerging component is not always straightforward. Further, because of the sparsity of Likes data, this approach is only viable using large datasets (Kosinski et al. 2016). Another analytical approach which may help prevent overfitting problems when performing personality prediction using large datasets is the least absolute shrinkage and selection operator algorithm, or LASSO regression (Tibshirani 1996). Using the LASSO approach, prediction is initially performed using all available Likes for the user, but only Likes that contribute significantly to the overall prediction are included in final model. Because of the large number of features used to perform prediction, interpretation of results is problematic and it is typically limited to the predictive accuracy of trained models over personality scores. Using this analytic approach, Youyou and colleagues (2015) demonstrated that score predictions of Big 5 traits derived from the analysis of Facebook-Likes can be more accurate than personal judgments of a user's friends, relatives, and even spouse. Furthermore, as shown by Torfarson and colleagues (2017) using the same analytical approach, prediction accuracy over personality seems to increase proportionally with the number of user Likes analyzed, with only 20 Likes needed to obtain personality scores as accurate as those provided by users' spouse.

An alternative approach that can help face the problem of the sparsity of Facebook Likes consists in analyzing collected data at the category-level, as opposed to the page-level. In doing this, Facebook pages that are registered in Facebook under the same category (e.g., "Retail company" category: *Amazon.com, ebay,it*, *Macy's*; Musician/Band category: *Frank Sinatra, Adele, Kraftwerk*) are counted in a single category indicator. Using this approach, Baik and colleagues (2016) examined Likes data by recoding 8.355 distinct Likes pages into 183 categories. This procedure allowed them to perform linear regression analyses with no variable selection, while also preserving interpretability of results. Using this approached they were able to predict users' extraversion with average accuracy ($r = 42$), and provide some insight on the association between the personality trait and specific user interests (e.g., extroverts were more likely to show interest in hotels, sports, and shopping/retail, whereas introvert users showed interested in musicians, bands, and games/toy categories).

Texts. The *user_posts* Graph API authorization allows access to user posting activity, including personal status updates and comments, and the number of Likes received on users' posts.

Studies have shown significant links between the Big Five personality traits and features extracted from Facebook texts (e.g., Hall and Caton 2017; Schwartz et al. 2013). For example, Extraversion has been shown to be positively associated with the frequency of use of words about family and friends, and positive emotions (Schwartz et al. 2013) and to be negatively associated with use of words indicating cognitive processes (insight words, Hall and Caton 2017; words indicating tentativeness, causation, inhibition, Schwartz et al. 2013). Coherent with findings about depression and language use (Eichstaedt et al. 2018). Neuroticism has been linked with increased use of words indicating use of 1st person singular pronouns, negative emotions, and coarse language (Schwartz et al. 2013); in turn the Agreeableness trait has been linked to increased positive emotion words (Hall and Caton 2017; Schwartz et al. 2013). Furthermore, Garcia and Sikstrom (2014) explored associations between the Dark Triad personality traits, i.e., Machiavellianism, Narcissism, and Psychopathy, and textual features extracted from Facebook texts. Findings showed that Psychopathy was the personality trait most easily predictable from the semantic content of status updates. Results also showed that individuals with high levels on the Psychopathy and Narcissism traits posted more negative words in their Facebook posts, and published more "atypical" content when compared to individuals with low scores on these traits.

For the purpose of personality prediction, most studies have extracted features from texts using two text analyses approaches: the more traditional *closed-vocabulary* analysis and the recently emerging *open-vocabulary* analysis. Closed-vocabulary analysis has a long history in psychological science and can be viewed as theory-driven approach that consists of scoring language data according to predetermined semantic categories. One of the most popular instruments to apply this kind of approach is the Linguistic Inquiry and Word Count (LIWC) software, which has been developed over the past 20 years to measure multiple dimensions by computing the relative frequency of word categories (Pennebaker et al. 2015; Tausczik and Pennebaker 2010). LIWC allows the scoring of text documents based on a set of predetermined categories ranging from parts of speech (e.g., use of pronouns, numbers, punctuation), emotional expression (e.g., positive or negative emotions, anger, sadness), cognitive processes (e.g., insight, discrepancy), to social processes (e.g., friends, family), and personal concerns (e.g., body, death, money, occupation).

In contrast, the more recent open-vocabulary analysis employs data driven analytic approaches to explore the distribution of topics, words, and phrases naturally occurring in analyzed texts; thus producing results that are not limited by predetermined categories (Schwartz and Ungar 2015). For this reason, the open vocabulary approach is particularly suited for the analyses of alternative forms of communication, such as use of abbreviations (e.g., OMG, IMHO, NSFW), as well as pictorial symbols (e.g., emoticons, emoji), which represent a significant component of modern computer-mediated communication. Some of the most used approaches for performing open vocabulary analysis on Facebook texts are Latent Semantic Analysis (Dumais 2004)

Table 8.1 Personality and Facebook language: closed-vocabulary (LIWC) correlates of neuroticism (n = 296, Correlations significant at $p < 0.05$)

LIWC category	r
I. Standard linguistic dimensions	
Negations	0.15
II. Psychological processes	
Affective processes	
Optimism	−0.15
Negative emotions	0.20
Anger	0.12
Sadness	0.28
Cognitive processes	
Possibility	0.18
Certainty	−0.13
Social processes	
Family	−0.15
Personal concerns	
Money and financial issues	−0.14
Body states, symptoms	0.12

and Latent Dirichlet Allocation (Blei et al. 2003) algorithms. Both approaches have been used to infer the semantic and topical content of Facebook texts in studies exploring the link between personality and language use (e.g., Schwartz et al. 2013; Garcia and Sikström 2014). Despite the advantages linked to their use, these approaches generally require large datasets and emerging results are typically harder to interpret than those provided by closed-vocabulary analyses. Table 8.1 and Fig. 8.1 provide an illustrative example on how results from closed- and open-vocabulary analyses are usually presented when examining their association with personality scores. Presented results are based on the analyses collected on a sample of 296 adult Facebook users from Italy (Female = 67%, Age: M = 28.44, SD = 7.38, previously unpublished results), and show the correlation between Neuroticism (Ten Item Personality Inventory, Gosling et al. 2003) and LIWC closed-vocabulary features (Table 8.1) and LDA open-vocabulary features (Fig. 8.1) computed on users' status updates. Topics emerging from LDA analyses are depicted using word clouds in which words that are more strongly related to the topic are depicted with larger font size and darker tones. Findings using LIWC and LDA topics are coherent in showing that Neuroticism correlates with increased negative emotionality in Facebook posts, and appear to be negatively related to the expression of positive emotions. However, each approach can provide different insights on the specific forma or semantic language features associated with the examined trait. Based on presented results, it is worthy to note that, similarly to what it is usually observed in the literature, effect-size of correlations between personality and both closed- and open-vocabulary features, is generally quite low. However, as shown by Schwartz and

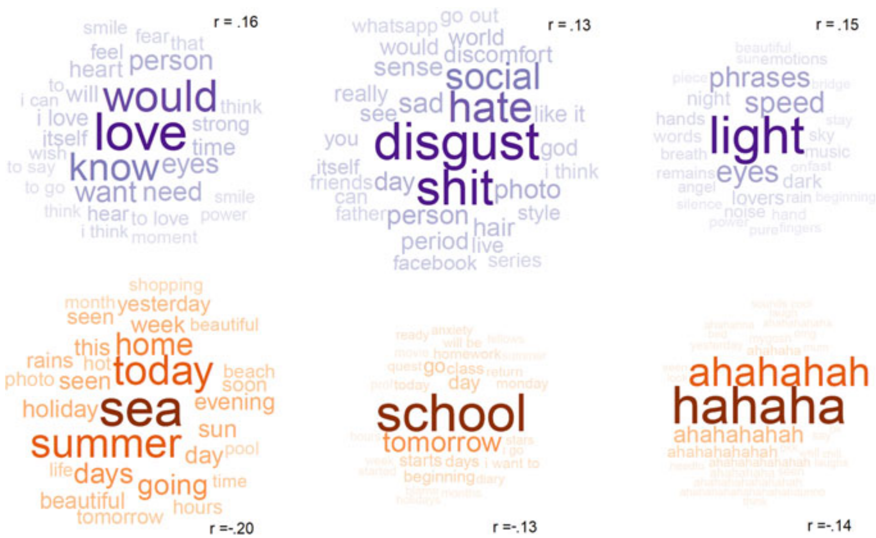

Fig. 8.1 Personality and Facebook language: open-vocabulary (LDA) correlates of neuroticism (n = 296, Correlations significant at p < 0.05)

colleagues (2013), when all extracted features are combined using predictive models, predictive accuracy is expected to improve significantly. Further, when compared to closed-vocabulary, open-vocabulary analysis has proven to yield additional insights and more in depth information about the behavioral characteristics of personality types beyond those that can be obtained by a traditional closed-vocabulary approach, resulting in increased prediction accuracy over personality (Schwartz et al. 2013).

Visual data. Sharing of pictures and videos is an increasingly frequent online activity and in the last few years new social media platforms have flourished focusing on the sharing of pictures and videos (e.g., Instagram, Snapchat) among users. This new phenomenon has also witnessed an increase on Facebook, as users are constantly provided with new features allowing for the proliferation of pictures and videos in their overall generated content, indicating a progressive shift from textual based interactions, to an increase in sharing of videos and photographs. Given the relative novelty of this phenomenon, only a few studies have explored the possible relations between visual data collected from Facebook, and personality, usually focusing on the analysis of user profile pictures (e.g., Celli et al. 2014; Torfason et al. 2016; Segalin et al. 2017). Access to the *default*, *user_photos* and *user_videos* Graph API authorizations allow researchers to inspect and download users' profile pictures, uploaded pictures, and videos. Celli and colleagues processed user profile pictures using a *bag-of-visual-words* approach, extracting 4096 non-interpretable visual features to perform predictions over personality scores. Prediction accuracy over personality traits was generally poor. However, they were able to show that extrovert and emotionally stable users post more frequently pictures in which they smile, and in which other people are included. On the other hand, introverts tend to appear alone, while Neurotics tend to post images without humans, and their pictures often feature close-up faces. Torfarson and colleagues, on the other hand, extracted information about specific facial features (e.g., eyeglasses, smiling, wearing lipstick) based on models trained on the CelebA dataset (Liu et al. 2015); based solely on features extracted from users' profile pictures, they observed a correlation of 0.18 between observed and predicted scores for the Big 5 personality traits. Finally, Segalin and colleagues (2017) extracted a large set of variables representing aesthetics-based features of images (i.e., color, composition, textual properties, and content), byte-level features, and both visual word and concept features extracted using other approaches (e.g., pyramid histogram of visual words; convolutional neural networks). In the study extroverts and agreeable individuals showed an increased inclination to post warm colored pictures and to exhibit many faces in their profile pictures; in turn, individuals high on neuroticism were more likely to post pictures of indoor places. As in the aforementioned studies, prediction accuracy was limited (~60% of correctly classified individuals), but still higher than that obtained in the study when using human raters. Overall, existing findings indicate that the accuracy of predicting personality achieved using visual data is still relatively limited compared to that achieved using other types of digital footprints (Azucar et al. 2018).

8.3 Establishing the Accuracy of Personality Predictions

Studies exploring the predictive power of Facebook digital footprints over personality vary significantly in the methods employed to assess such associations. Some studies implement simple bivariate analyses (e.g., zero-order correlation, independent samples t-test) examining the strength of associations between personality scores and numerical variables representing features extracted from digital footprints (e.g., Gosling et al. 2011; Panicheva et al. 2016), while other studies investigate the accuracy of personality predictions based of the mining of large set of features using predictive models (e.g., Kosinski et al. 2013; Celli et al. 2014). Other studies present both kinds of analyses (e.g., Schwartz et al. 2013; Farnadi et al. 2016).

Another important difference emerging from these studies relates to the use of validation techniques to avoid overfitting problems and support generalizability of results. Amongst the most used validation methods are the *holdout* method, the *k-fold* validation method, and the *leave-one-out* method. When using the holdout method, collected data is randomly split in two datasets of unequal size, a larger training set and a smaller test set, consisting of mutually independent observations. Analyses are first performed on the training set, resulting in a set of parameters or coefficients describing the association between features extracted from digital footprints, and personality scores. Then, the developed models are applied on the smaller test set using the estimated parameters or coefficients: Accuracy of personality predictions informs about the expected performance of the model on new, unseen observations. The *k*-fold validation method is similar, in that it also involves randomly splitting the dataset in a training set and a test set, but the process is repeated *k* times, resulting in *k* sets of results which are averaged to produce a single estimation of accuracy. Finally, in the leave-one-out method, the split is repeated for as many observations present in the dataset, i.e., the dataset is iteratively split so that only one observation is used to the test accuracy of predictions, while the remaining observations are used to estimate model parameters or coefficients. In general, *using k-fold validation and leave-one-out methods* is preferable over the *simple holdout* method (Kohavi 1995). As regards the number of folds, authors have suggested either using k = 5 and k = 10 folds when performing cross-validation over k = 2 folds, as using a larger number of folds is expected to decrease bias in estimating prediction errors (Rodriguez et al. 2010); however, it should be noted that as increasing the number of folds is only feasible using large datasets, as the large sample condition needs to be achieved in each of the fold (Wong 2015).

Most of the studies examining the predictive power of digital footprints collected from Facebook used a k-fold method to validate personality predictions (e.g., Golbeck et al. 2011; Bachrach et al. 2012; Quercia et al. 2012; Kosinski et al. 2013; Farnadi et al. 2016, 2018; Baik et al. 2016; Thilakaratne et al. 2016) followed by the holdout method (e.g., Celli et al. 2014; Schwartz et al. 2013). It is worthy to note that some authors did not employ a cross-validation technique in their studies, but they analyzed data from their whole samples (e.g., Gosling et al. 2011; Garcia and Sikström 2014). Caution should be used in interpreting their findings due to the limitations cited above, i.e. overfitting and lack of generalizability.

8.4 Accuracy of Personality Predictions Based on Facebook Data

Two recent meta-analytic studies have examined the literature aiming at estimating the overall prediction accuracy of digital footprints collected on a wide range of social media platforms (e.g., Facebook, Twitter, Sina Weibo, and Instagram) over users' individual characteristics. Settanni and colleagues (2018) identified 38 papers investigating associations between digital footprints and a set of individual characteristics, including personality (e.g., traits from the Big Five and the Dark Triad personality models), psychological well-being (e.g., satisfaction with life, depression), and intelligence. Overall, based on findings from a subset of 18 studies, the estimated overall accuracy in predicting personality, computed as a meta-analytical correlation was moderate (r = 0.34). Further, the results of the meta-analysis showed that the overall accuracy in predicting personality was lower than the accuracy in predicting psychological well-being (r = 0.37), but higher than what was computed for the prediction of intelligence (r = 0.29). In turn, the meta-analysis by Azucar and colleagues (2018) examined literature focusing on studies presenting associations between digital footprints and traits from the Big Five model—i.e., Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Based on prediction results presented in 16 independent studies, Extraversion appears to be associated with the highest overall prediction accuracy (r = 0.40), followed by Openness (r = 0.39), Conscientiousness (r = 0.35), Neuroticism (r = 0.33), and Agreeableness (r = 0.29). In the aforementioned meta-analyses, a set of meta-regression was conducted to recognize factors influencing prediction accuracy, finding that the accuracy improves when models include information about users' demographics and more than one type of digital footprints. In both meta-analyses, examined studies referred to a conceptualization of personality as a multi-dimensional construct; hence, reported results should not be interpreted as indicating accuracy in predicting discrete personality types.

Given the relevance of Facebook in the social media world, we re-estimated overall prediction accuracy reported in the two cited meta-analyses, including only those studies presenting predictions based on Facebook data. Very similar results emerged, with r values ranging from 0.33 (Neuroticism) to 0.43 (Extraversion), and an overall correlation equal to 0.34, 95% CI [0.24–0.44] indicating that the use of data extracted from differing social media platforms is not expected to have a significant effect on the accuracy of personality predictions. As noted by Kosinski and colleagues (2013) this correlation size corresponds to the "personality coefficient" (a Pearson correlation ranging from 0.30 to 0.40; Meyer et al. 2001; Roberts et al. 2007), which is the upper limit of correlations between behaviors and personality traits reported in past psychological studies. Among the examined traits, Extraversion appears to be most easily predictable based on the examination of digital footprint from Facebook, a finding which is compatible with findings emerging from studies exploring other sources of digital footprints (e.g., smartphone usage, Stachl et al. 2017). Still, upon inspecting these results, it is important to note that the average prediction accuracy reported by existing studies is still quite limited. For this reason, reliability of individual personality predictions obtained by mining digital footprint is still quite low, in particular when compared with that obtainable with traditional self-report assessments, limiting their use of predicted scores for assessment purposes.

8.5 Conclusions

In this chapter, we presented an overview of studies examining the feasibility of inferring individual differences in personality of Facebook users based on the analyses of their digital footprints (e.g., user demographics, texts, Facebook Likes, and pictures). Published studies vary significantly in employed analytical approaches, both in terms of methods used for extracting features from raw social media data, performing predictions, and validating results. Overall, the accuracy of personality predictions based on the mining of digital footprints extracted from Facebook appears to be moderate, and similar to that achievable using data collected on other social media platforms. Given the relatively recency of this area of research, and the rapid evolution of data mining techniques, we expect accuracy of personality prediction to improve in the near future. The ability to use digital footprints for the unobtrusive assessment of personality traits can represent a rapid, cost-effective alternative to surveys to reach large online populations, an approach which can be beneficial for academic, health-related, and commercial purposes pursued in the online environment (e.g., improve the efficacy of online health-related messages and interventions, enhance online recommender systems, improve user experiences, enhance efficacy of advertising by tailoring online message to personality attributes, including political messages, Matz et al. 2017).

8.5.1 Future Directions and Ethical Concerns

Meta-analyses conducted to determine the predictive power of social media data on psychological characteristics in general, and in particular on personality traits, revealed that collecting information from multiple sources (e.g. from pictures and text) and different social media platforms, permit to achieve greater predictive power. This means that in the near future, the aggregation of features extracted from different types of data and the inclusion of data from different social media platforms, or from other sources, such as wearables (e.g., iwatch, runkeeper, etc.) or mobiles, will probably lead to relevant improvements in the predictive power of these kinds of models. Furthermore, the progressive expansion and complexification of individuals' online activities will support the creation of an increasing number of datasets, easily available for the development of predictive models. It is foreseeable that the development of new and more efficient approaches to data collection, integration, and analysis (e.g., using deep learning algorithms) will contribute to making predictions more accurate and reliable, extending their reach well beyond the field of personality traits, towards the prediction of more specific characteristics, behaviors, and even biological features (Montag et al. 2017; Sariyska et al. 2018). The acquisition of these new capabilities will raise important ethical issues that cannot be underestimated.

Social media data may be used in ways that surpass what users intend, or understand, when they give consent to their collection. Apparently innocuous data points may be and have been used to reveal information that users might expect to stay private. These predictions can have negative consequences for social media users: First, predicted traits can be used to make decisions relative to single Facebook users, without their explicit consent to disclose such characteristics (e.g., in hiring procedures); Second, as recently highlighted by Matz and colleagues (2017), psychological targeting procedures might be developed and aimed at manipulating the behavior of large groups of people, without the individuals being aware of it.

Given the possibility of using raw data to infer relevant individual characteristics, the need is emerging for a more careful consideration of ethical challenges related to the use of data extracted from Facebook or other social media. It is worthy to note that, while research in medicine and psychology is routinely subjected to IRB ethical approvals, the same does not apply for computer science. Same as in clinical disciplines, computers scientists should also develop and apply ethical restrictions when they do research in this field, and research projects should adhere to the principle of beneficence: the good of research participants should be taken in high consideration and influence the assessment of risks versus benefits when planning a research. As recently noted in a Nature editorial (2018) on the Cambridge Analytica scandal, the fact that data are there should not be a sufficient reason to exploit these in order to conduct research.

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Chapter 9
Orderliness of Campus Lifestyle Predicts Academic Performance: A Case Study in Chinese University

Yi Cao, Jian Gao, and Tao Zhou

Abstract Different from the western education system, Chinese teachers and parents strongly encourage students to have a regular lifestyle. However, due to the lack of large-scale behavioral data, the relation between living patterns and academic performance remains poorly understood. In this chapter, we analyze large-scale behavioral records of 18,960 students within a Chinese university campus. In particular, we introduce orderliness, a novel entropy-based metric, to measure the regularity of campus lifestyle. Empirical analyses demonstrate that orderliness is significantly and positively correlated with academic performance, and it can improve the prediction accuracy on academic performance at the presence of diligence, another behavioral metric that estimates students' studying hardness. This work supports the eastern pedagogy that emphasizes the value of regular lifestyle.

Keywords Computational social science · Orderliness · Academic performance · Human behavior

9.1 Introduction

Asian traditional culture considers regularity as an important and valuable personal trait. Therefore, in addition to being diligent, parents and teachers in most Asian countries ask students to live disciplined and regular lives. Accordingly, a hard-working and self-disciplined student is usually recognized as a positive model. To maintain large-size classes, teachers in Far East Asia create the highly disciplined classes (Ning et al. 2015; Baumann and Krskova 2016), while western teachers

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_9

rarely emphasize discipline in class or regularity in life. In 2015, BBC broadcasted a documentary about an attempt of Chinese-style education in the UK (BBC 2015), where Chinese teachers and UK students were maladjusted to each other at the beginning but English pupils taught by Chinese teachers eventually got better scores than their peers in a series of exams.

Although eastern and western have different pedagogies, they face the same challenge in education management, that is, to uncover underlying ingredients affecting students' academic performance. Previous studies have demonstrated that educational achievement is related to health conditions (Santana et al. 2017; Hoffmann 2018), IQ (Duckworth and Seligman 2005) and even to molecular genetic markers (Okbay 2016; Selzam et al. 2017). For example, scientists identified 74 genome-wide significant loci associated with the years of schooling (Okbay 2016). Since students' mentality and behavior are more interventional, the majority of studies concentrate on psychological and behavioral issues (Conard 2006). Experiments have demonstrated correlations between academic performance and personality (Chamorro-Premuzic and Furnham 2003; Poropat 2014). In particular, conscientiousness is the best predictor of GPA, while agreeableness and openness are of weaker effects (Vedel 2014). Behaviors of students are also associated with their academic performance, for example, students with more class attendance (Credé et al. 2010; Kassarnig et al. 2018), longer time on study (Grave 2011; Cattaneo et al. 2017), good sleep habits (Taylor et al. 2013; Urrila et al. 2017) and more physical activity (Erwin et al. 2017) perform better on average.

This said, it is still debated in the scientific community if a regular lifestyle in general represents an important prerequisite for academic study or not. One of the reasons for this ongoing debate is that, statistical validation of these observations based on large-scale behavioral data remains lacking. Traditional framework relies on data coming from questionnaires and self-reports, which usually contains a small number of participants (Vedel 2014) and suffers from being biased by the tendency to answer in a social desirable fashion (Fisher 1993). Second, previous studies rarely isolate regularity in living patterns from diligence in studies. As a more regular studying pattern may be correlated with a longer studying time, it is hard to distinguish their independent effects on academic performance. So far, to our knowledge, a quantitative relationship between regularity in everyday life and academic achievement has not been demonstrated. Fortunately, rapid development of information technologies has made it possible to study students' activities in an unobtrusive way by collecting their digital records through smartphones (Wang et al. 2014), online course platforms (Brinton et al. 2016), campus WiFi (Zhou et al. 2016), and so on (Gao et al. 2019). These large-scale extracurricular behavioral data offer chances to quantify the regularity of campus lifestyle and explore its relation to academic performance.

In this chapter, we present a case study on the relation between students' campus lifestyles and their academic performance. Through campus smart cards, we have collected the digital records of 18,960 undergraduate students' daily activities including taking showers, having meals, entering/exiting library and fetching water. Accordingly, we proposed two high-level behavioral characters, orderliness

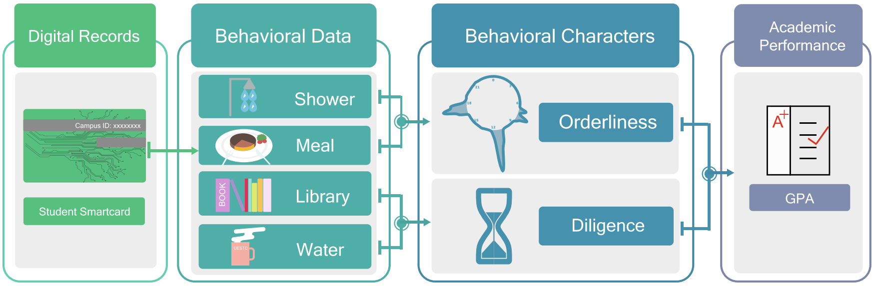

Fig. 9.1 Illustration of the methodology to reveal the relation between campus lifestyle and academic performance. Four types of behavioral records are collected by campus smart cards. Taking showers and having meals are used to measure orderliness, which represents the regularity level of campus life. And entering/exiting library and fetching water are used to measure diligence for which the reason is that cumulative occurrences of these behaviors in study places is naturally recognized as the total efforts taken on studying hardness. Correlations between behavioral features and academic performance are analyzed, and the predictive powers of orderliness and diligence are compared

and diligence (see Fig. 9.1 for the methodology). The orderliness factor is a novel entropy-based metric that measures the regularity of campus life, which is calculated based on temporal records of taking showers and having meals. The diligence factor is roughly estimated based on the cumulative occurrences of entering/exiting library and fetching water. Empirical analyses demonstrated that academic performance (GPA) is significantly correlated with orderliness and diligence. Moreover, orderliness can improve the prediction accuracy on academic performance at the presence of diligence. Some primary results have been published in a recent article (Cao et al. 2018), and the present chapter is an extension with more detailed analyses.

9.2 Data and Metrics

9.2.1 Data Description

In most Chinese universities, every student owns a campus smart card which is used for student identification and serves as the unique payment medium for many on-campus consumptions. For example, there are toll gates in shower rooms, where students have to keep the smart card inserted during the shower. Here, we introduce a specific case study in a Chinese university, the *University of Electronic Science and Technology of China* (UESTC), which provides on-campus dormitories to all undergraduate students and in principle does not allow students to live off-campus. Therefore, smart cards record large volume of behavioral data in terms of students' living and studying activities. Accordingly, we have collected digital records of

$N = 18{,}960$ undergraduate students' daily activities from September 2009 to July 2015, covering the period from the beginning of their first year to the end of their third year. The data includes the purchase records for showers ($n = 3{,}151{,}783$) and meals ($n = 19{,}015{,}773$), the entry-exit records in library ($n = 3{,}412{,}587$) and fetching water records in teaching buildings ($n = 2{,}279{,}592$). GPAs of students in each semester are also collected.

9.2.2 Orderliness

We calculate orderliness based on two behaviors: taking showers in dormitories and having meals in cafeterias. Indeed, the meaning of orderliness is twofold, say timing and order. The happening times of the same kind of events should be close to each other, for example, having breakfast at about 8:00 is more regular than between 7:00 and 9:00. The temporal order of different events should also be regular, for instance, having meals following the order breakfast → lunch → supper → breakfast → lunch → supper is more regular than breakfast → supper → lunch → supper → breakfast → lunch. With these insights, we turn to the mathematical formula of orderliness. Considering a student's specific behavior within total n recorded actions happening at time stamps $\{t_1, t_2, \ldots, t_n\}$, where $t_i \in [00{:}01, 24{:}00]$ denotes the precise time with resolution in minutes. We first arrange all actions in the order of occurrence, namely, the i-th action happens before the j-th action if $i < j$, while we ignore the date information. Then, we divide one day into 48 time bins with a 30 minutes step (specifically, 0:01–0:30 is the 1st bin, 0:31–1:00 is the 2nd bin, …), and map the time series $\{t_1, t_2, \ldots, t_n\}$ into a discrete sequence $\{t'_1, t'_2, \ldots, t'_n\}$, where $t'_i \in \{1, 2, \ldots, 48\}$. If a student's starting times of five consecutive showers are {21:05, 21:33, 21:13, 21:48, 21:40}, the corresponding binned sequence is $\mathcal{E} = \{43, 44, 43, 44, 44\}$. Next, we apply the actual entropy (Kontoyiannis et al. 1998; Xu et al. 2019) to measure the orderliness of any sequence $\mathcal{E}$. Formally, the actual entropy is defined as

$$S_{\mathcal{E}} = \left(\frac{1}{n} \sum_{i=1}^{n} \Lambda_i \right)^{-1} \ln n, \tag{9.1}$$

where Λ_i represents the length of the shortest subsequence which starts from t'_i of $\mathcal{E}$ and has never appeared previously. Note that we set $\Lambda_i = n - i + 2$ if such subsequence cannot be found (Xu et al. 2019). Finally, we define orderliness as $O_{\mathcal{E}} = -S_{\mathcal{E}}$ and calculate regularized orderliness by normalizing $S_{\mathcal{E}}$ via *Z-score* (Kreyszig 2010):

$$O'_{\mathcal{E}} = \frac{O_{\mathcal{E}} - \mu_O}{\sigma_O} = \frac{\mu_S - S_{\mathcal{E}}}{\sigma_S}, \tag{9.2}$$

where μ_O and σ_O are the mean and standard deviation of orderliness O, μ_S and σ_S are the mean and standard deviation of actual entropy S, and $O'_{\mathcal{E}}$ is the regularized orderliness for the student with binned sequence $\mathcal{E}$. The larger orderliness corresponds to higher regularity of a student's campus lifestyle.

9.2.3 *Diligence*

Diligence measures to what extent people take efforts to strive for achievements. As an important behavioral character, diligence is intuitively related to students' academic performance. Due to the lack of ground truth, however, it is difficult to quantify students' diligence. Here, we roughly estimate diligence based on two behaviors: entering/exiting the library, and fetching water in teaching buildings. Specifically, we use a student's cumulative occurrences of library entering/exiting and water fetching as a rough estimate of his/her diligence. Basically, self-studying and borrowing books are the most common purposes of going to the library, while attending courses usually take place in the teaching buildings. As teaching buildings have no check-in devices or entry terminals like the library, we use records of water fetching as the proxy.

9.3 Result

9.3.1 *Validation of Behavioral Characters*

Figure 9.2a, b present the distributions of actual entropies on taking showers and having meals, respectively. The broad distributions guarantee the discriminations of students with different orderliness. For student H with very high orderliness (at the 5th percentile) and student L with very low orderliness (at the 95th percentile), we notice that student H takes most showers around 21:00 while student L may take showers at any time in a day (Fig. 9.2c). We observe the similar discrepancy on having meals (Fig. 9.2d). Figure 9.2e, f present the distributions of cumulative occurrences for entering/exiting the library and fetching water. The two distributions are both broad, showing that the two diligence metrics can distinguish students with different levels of studying hardness.

We next explore the consistency and dependence of the two behavioral characters. As either orderliness or diligence is measured by two types of behavioral records, their intra correlations should be high if they are properly measured. That is, orderliness-meal should be correlated with orderliness-shower, and diligence-water should be correlated with diligence-library. Moreover, the effect of orderliness should be isolated from diligence, i.e., their inter correlations should be low. Figure 9.3 presents the Spearman's correlation matrix between each pair of behavioral features. The intra correlations are all positive and significant, with the correlation $r = 0.226$ between two orderliness metrics and $r = 0.262$ between two diligence metrics. Moreover, if

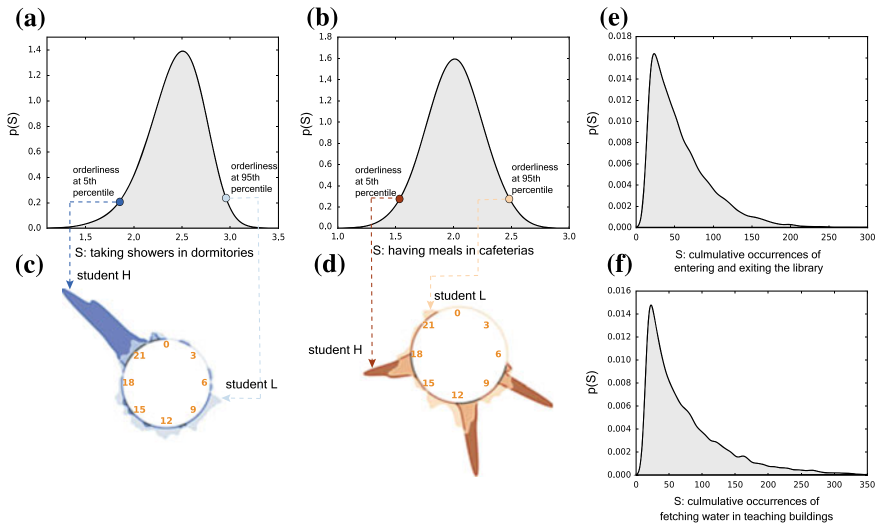

Fig. 9.2 **Distributions of actual entropies and cumulative occurrences**. Distributions $p(S)$ of students in taking showers (**a**) and having meals (**b**). The x-axis represents the actual entropies S, calculated in each semester. The broad distributions guarantee the discriminations of students with different orderliness. The behavioral clocks of two students at the 5th percentile and the 95th percentile are shown for taking showers (**c**) and having meals (**d**), where student H has high orderliness and student L has low orderliness. Distributions $p(C)$ of students in entering/exiting library (**e**) and fetching water (**f**), calculated in each semester. The broad distributions distinguish students with different diligence levels

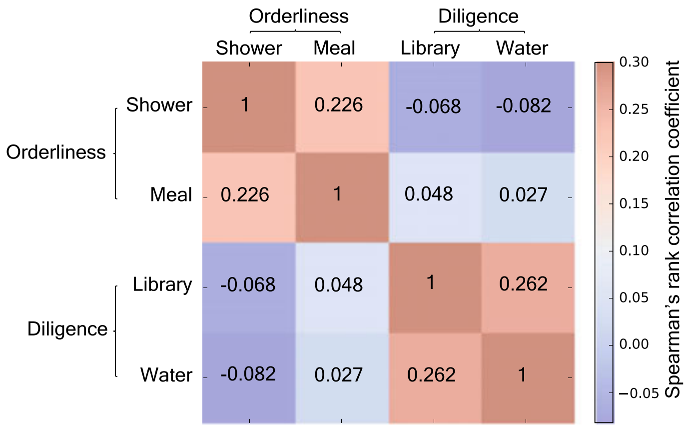

Fig. 9.3 **Correlations among behavioral features**. Shower and Meal are the two orderliness features, while Library and Water are the two diligence features. The color denotes the corresponding Spearman's rank correlation coefficient. Significance level: all p-values are less than 10^{-15}

orderliness provides additional information to diligence, the correlation between any pair of orderliness metric and diligence metric should be insignificant. As shown in Fig. 9.3, all inter correlations are close to 0, suggesting the absence of significant correlation between orderliness and diligence. These results validate the robustness of the two behavioral characters and demonstrate their independence.

9.3.2 Correlation Analysis

Students of higher orderliness and diligence are expected to have better grades. Here, we empirically assessed how students' orderliness and diligence are related to their academic performance (GPA). The regularized GPA for student i is defined as $G_i' = (G_i - \mu_G)/\sigma_G$, where G_i is his/her GPA, and μ_G and σ_G are the mean and standard deviation of G for all considered students.

Figure 9.4a, b present how regularized GPA is positively correlated to regularized orderliness-shower and regularized orderliness-meal, respectively. As the relationships between orderliness and GPA are not simply linear, we apply the well-

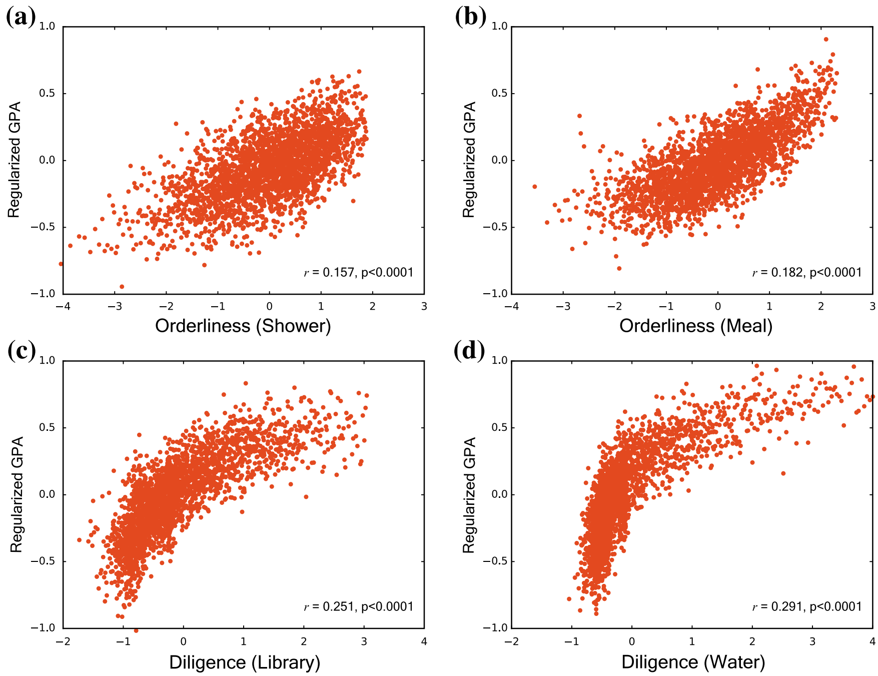

Fig. 9.4 Relations between behavioral features and academic performance. How regularized GPA is positively correlated with **a** regularized orderliness-shower, **b** regularized orderliness-meal, **c** regularized diligence-library, and **d** regularized diligence-water. The corresponding Spearman's rank correlation coefficients and the level of statistical significance are shown in each plot

known Spearman's rank correlation coefficient (Spearman 1904) to quantify the strength of correlation. Results show that the correlation between orderliness-meal and GPA is $r = 0.182$, and the correlation between orderliness-shower and GPA is $r = 0.157$, both with statistical significance $p < 0.0001$. Analogously, Fig. 9.4c, d present how regularized GPA is positively correlated to regularized diligence-library and regularized diligence-water, respectively. The correlation between diligence-library and GPA is $r = 0.291$, and the correlation between diligence-water and GPA is $r = 0.251$.

As a summary, the two behavioral characters are significantly correlated to academic performance with correlations being about 0.2. The Spearman's rank correlations for diligence (library and water) are stronger than for orderliness (shower and meal), while eyeballing the data suggests the opposite (Fig. 9.4). As a robustness check, we additionally calculated the Pearson correlation coefficients. Results showed that correlations for diligence remain stronger than for orderliness. The visual discrepancy may be because the data points are dispersive. As orderliness is largely independent to diligence, the results suggest their independently potential effects on students' academic performance.

9.3.3 Predictive Analysis

The significant correlations between behavioral features and GPA imply that orderliness and diligence can be used as different feature classes to predict students' academic performance. Here, we predict the ranks of students' semester grades by applying a well-known supervised learning-to-rank algorithm named RankNet (Burges et al. 2005). Given a feature vector $\mathbf{x} \in \mathbb{R}^p$ of each student, RankNet tries to learn a scoring function $f : \mathbb{R}^p \to \mathbb{R}$, so that the predicted ranks according to f are as consistent as possible with the ground truth. The consistence is measured by the cross entropy between the actual probability and the predicted probability. Based on the scoring function, the predicted probability that a student i has a higher GPA than another student j (denoted as $i \triangleright j$) is defined as $P(i \triangleright j) = \sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j))$, where $\sigma(z) = 1/(1 + e^{-z})$ is a sigmoid function.

We consider a simple regression function $f = \mathbf{w}^T\mathbf{x}$, where $\mathbf{w}$ is the vector of parameters. The cost function of RankNet is given by

$$\mathcal{L} = -\sum_{(i,j):i \triangleright j} \log \sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j)) + \lambda \Omega(f), \tag{9.3}$$

where $\Omega(f) = \mathbf{w}^T\mathbf{w}$ is a regularized term. Given all students' feature vectors and their ranks, gradient decent is applied to minimize the cost function. The gradient of the lost function with respect to parameter $\mathbf{w}$ in f is

Table 9.1 AUC values for the GPA prediction. The abbreviations O, D and O + D stand for utilizing features on orderliness only, on diligence only and on the combination of orderliness and diligence, respectively

Features	Semester 2	Semester 3	Semester 4	Semester 5
O	0.618	0.617	0.611	0.597
D	0.630	0.655	0.663	0.668
O + D	0.668	0.681	0.685	0.683

$$\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \sum_{(i,j):i \rhd j} (\sigma(f(\mathbf{x}_i) - f(\mathbf{x}_j)) - 1) \left(\frac{\partial f(\mathbf{x}_i)}{\partial \mathbf{w}} - \frac{\partial f(\mathbf{x}_j)}{\partial \mathbf{w}} \right) + \lambda \frac{\partial \Omega(f)}{\partial \mathbf{w}}. \quad (9.4)$$

The prediction accuracy is evaluated by AUC value (Hanley and McNeil 1982), which is equal to the percentage of student pairs whose relative ranks are correctly predicted. The AUC value ranges from 0 to 1 with 0.5 being the random chance, therefore to which extent the AUC value exceeds 0.5 can be considered as the predictive power.

We train RankNet based on the extracted orderliness and diligence features in one of the first four semesters and predict students' ranks of grades in the next semester. We use the abbreviations O, D and O+D to stand for utilizing features on orderliness only, on diligence only and on the combination of orderliness and diligence, respectively. Table 9.1 presents the results of AUC values under different feature combinations, where the column semester j represents the case in which we train the data of semester $j - 1$ and predict the ranks of grades in semester j. Obviously, both orderliness and diligence are predictive to academic performance, and orderliness can improve the prediction accuracy at the presence of diligence, showing its independent role in facilitating academic studying.

9.4 Discussion

Large parts of the Eastern world value regularity in campus lifestyle, while large parts of the Western world tend to provide a more unconstrained lifestyle to students. The disparity in educational philosophy between these different parts of the world may originate from their culture differences. Yet, the core question is whether regularized campus lifestyle is helpful to achieve higher academic performance. To answer this question, we presented the data-driven case study based on large-scale behavioral records of students' living and studying activities in a Chinese university campus (Cao et al. 2018). Specifically, we calculated orderliness based on temporal records of taking showers and having meals, which is not directly related to studying activities. Empirical analyses show that academic performance is significantly and positively correlated with orderliness. Moreover, orderliness can remarkably improve the accuracy of academic performance prediction even at the presence of diligence, suggesting the independent predictive power of orderliness.

Our work not only provides a quantitatively understanding of the relationships between students' behavioral patterns and academic performances, but probably also takes a significant step towards better educational management. On the one hand, education administrators could design personalized teaching and caring programs for individuals with different behaviors. For example, recent works have discussed the prediction of course failures and dropping out for K12 education (Kindergarten and the 1–12 grades) (Jayaprakash et al. 2014; Lakkaraju et al. 2015), and thus teachers could pay more attentions in advanced to those students who may develop difficulties in studying.

On the other hand, education managers can detect students' undesirable abnormal behaviors from traced data (e.g., Internet use disorder (IUD) Montag and Reuter 2017; Brand et al. 2016; Peterka-Bonetta et al. 2019) and implement interventions in time. IUD is negatively correlated with academic performance (Akhter 2013; Khan et al. 2016), and IUD is among the most important reasons resulting in the failure of college study in China. Two issues need to be discussed in the context of IUD, formerly also known as Internet addiction. Firstly, the sharp fall of exam performance or even failure of many courses appears about one or two semesters after developing IUD. Secondly, it requires a long time (usually a few months) for a student to rebuild learning ability after proper treatment of IUD.

Therefore, a student's academic performance would not drop immediately, while IUD immediately will impact on the student's behaviors (e.g., absence from classes). Students suffering from IUD demonstrated largely different behavioral patterns compared to those not suffering from IUD, for example, students with IUD have irregular bedtimes and dietary behavior (Kim et al. 2010), and their diligence and orderliness usually dramatically decline. Accordingly, it might be possible to establish models being able to predict whether students are more prone to develop IUD, and thus those problem students can be helped as soon as possible.

Even though traditional questionnaire surveys are limited by sample sizes and suffering from response biases such as tendencies to answer in a social desirable way (Paulhus and Vazire 2007), these two methodologies can complement and benefit each other. The use of unobtrusive digital records is helpful in improving the quality of questionnaires (Montag et al. 2016), meanwhile the assessment of psychological characteristics related to a target behavior can be also complemented by self-report questionnaires, e.g., assessing conscientiousness, which would have been of interest also in the present work. Indeed, it has been shown that is possible to infer self-reported personality and other private attributes from available online information such as Facebook-Likes (Kosinski et al. 2013; Youyou et al. 2015). Moreover, it is promising to establish a causal link between behavioral features and academic performance through designing controlled experiments. We are expecting psychologists and computer scientists to work together on such a promising research endeavor in the near future (Gao et al. 2019).

As we know from our culture, Chinese universities value disciplinary behaviors (Baumann and Krskova 2016). However, whether orderliness will be of same positive quality for academic study performance in other countries remains an open question. On the one hand, orderliness relies in our work on campus activities while students in other countries may live off-campus or spend a considerable portion of time doing part-time jobs, resulting perhaps in lower orderliness (but such differences between "West" and "East" need to be systematically evaluated on an empirical level and we explicitly state this to be a working hypothesis). On the other hand, it is difficult to isolate orderliness from the capacity to follow the teacher's advice (whatever that is) in and out of classes. Although previous studies have shown that better classroom discipline leads to better academic performance (Ning et al. 2015), whether a student's capacity to follow advice is related to her/his achievements is not clear or may be also attributable to other person characteristics including intelligence.

We hope that recent works leveraging large-scale behavioral data analysis and machine learning techniques also find its way into pedagogical sciences (Kassarnig et al. 2018; Wang et al. 2014; Gao and Zhou 2016). Indeed, uncovering factors that affect educational outcome play a significant role in future quantitative and personalized education management and could help to improve the schooling process.

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Chapter 10
From Outside In: Profiling, Persuasion and Political Opinion in the Age of Big Data

Saurabh Dhawan and Simon Hegelich

Abstract To the extent that there are measurable factors, rules and conditions—whether they be psychological, biological or socioeconomic—that shape political beliefs, preferences and biases, and to the extent their individualized measurement is accessible to political actors, they make possible surreptitious manipulation of individual political opinions and threaten long held ideas of personal and political autonomy. This makes a suspect of every new insight in digital phenotyping, psychoinformatics and political data science for its potential for abuse in individualization of propaganda and political manipulation. We review recent research into digital phenotyping, especially psychographic profiling, and its use in personalizing persuasive messages. We posit that individual political affinity can at least partially be seen as a stable phenotype that is identifiable using personal digital trace data and discuss the political implications of microtargeting and personalized persuasive communication based on such phenotyping.

Keywords Psychographics · Profiling · Microtargeting · Politics · Persuasive communication · Propaganda · Autonomy

10.1 Introduction

Wilhelm Dilthey, the nineteenth century German philosopher, argued that hermeneutics, the theory and methodology of interpretation, required going 'from outside in'—from the outside of other people to their inner being using personal data they offered: writing, artistic productions, speech and deeds (Dilthey 1900; Grayling 2019). Digital phenotyping, psychoinformatics and other allied sciences (Jain et al. 2015; Montag et al. 2016; Baumeister and Montag 2019) add likes, tweets, comments, call records, web searches, social graphs, emails, texts, physical activity logs, location tracking, heart rate, sleep records, and even typing kinematics to the mix but aim to do much the same—to go from outside in. While even until the late twentieth century, few

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_10

produced a corpus of personal data large enough that it offered insights back into their individual selves, now nearly every human adult does (86.6% of the population in developed countries and a total of 4.1 billion people worldwide are internet users, Source: ITU 2019). This boomerang-like effect of personal digital trace data—the data that an individual leaves online is used to profile her and then finds its way back to her as individually targeted manipulation—is bound to have implications for political systems where power is derived from the choices made by individuals. Indeed, an Oxford University report (Bradshaw and Howard 2018) stated that since 2010, political parties and governments alone have spent more than half a billion dollars on the research, development, and implementation of psychological operations and public opinion manipulation over social media.

10.2 The Fast-Expanding Affordances of Digital Trace Data

One would be forgiven for being under the impression that, when online, one can clearly choose what to reveal e.g., photos, profession, or musical preferences, and what not to reveal e.g., sexual orientation or political views, but often enough the distinction is blurred as the former can be used to predict the later. We find it useful to conceptualize the predictive possibilities that digital trace data offers by borrowing the term 'affordance' from cognitive psychology and robotics literature. The concept, first introduced by Gibson (1966), to explain how there are 'meanings' and 'action-possibilities' inherent in things in the environment that can be automatically perceived by an observer. We define data affordance as information inherent in a given set of digital trace data that can be reliably predicted by an observer (a human analyst or an algorithm) and linked to action-possibilities. In other words, it refers to possibilities for prediction and action that digital trace data offers to an observer with a given set of analytical capabilities. Accordingly, we distinguish between two forms of data affordance: prediction and action affordance. For instance, for a microtargeting algorithm, the predictive-possibility offered by Facebook Likes data would be the psychological profiles that could be built from it, which in turn would drive the action-possibility of targeted advertising.

A valuable insight that this perspective offers is that affordance is not a fixed, static quality but can grow with observer's capability even as the object or data remains constant—the primary affordance of a coffee mug is as a utensil for holding a beverage but it can also be used as a container for pencils or cutlery, as a pot for growing small plants, as a cast to build sand castles etc. Similarly, it is worth noting that data affordance of an existing set of data to an analyst is not fixed but will continue to grow with advances in machine learning and artificial intelligence on one hand and domain knowledge on another. For instance, at the point someone uploaded a facial image online or agreed to the term of service of a given company, it might have been done with the understanding that the affordance of the image was restricted to identification. Recently, however, researchers have claimed it is possible to use facial images to also predict sexual orientation (Wang and Kosinski 2018) and political affinities (Kosinski 2021). The prediction affordance of the same facial image would expand with these findings from only identification to include sexual orientation and political affinities, information that the user had never consented to share.

10.3 Prediction Affordances of Digital Trace Data: Profiling

The European General Data Protection Regulation defines 'profiling' as: 'any form of automated processing of personal data […] to analyze or predict aspects concerning that natural person's performance at work, economic situation, health, personal preferences, interests, reliability, behavior, location or movements' (Privacy International 2020). Wells (1975) offered the following operational definition for psychographic profiling which remains apt: 'quantitative research intended to place consumers on psychological—as distinguished from demographic—dimensions.' While its application to political manipulation brought it to limelight only recently, psychographic profiling got its start in marketing research in the 1960's after the seminal study by Koponen (1960), when researchers started trying to juxtapose consumer behavior with scores on personality questionnaires (Wells 1975). Whereas demographics explained 'who' the consumer was, psychographics attempted to examine 'why' she might buy a given product by adding information about personality traits, needs, values, attitudes and the so called AIO data (activities, interests, opinions). In the past, while psychological dimensions were judged by personal interviews or by asking people to fill in standardized psychological inventories, which is both expensive and difficult to scale, the scope and intrusiveness of psychographics remained limited. However, the fundamental reorganization of human information and communication systems that happened with the internet, smartphones and social media companies, and the newfound corporate ownership of detailed personal data on large sections of population, also fundamentally changed the field of psychographics. Researchers in diverse fields ranging from marketing to healthcare found that personal digital trace data could be used to assess psychological dimensions and could enable building of personalized psychographic profiles for large sections of the population (Azucar et al. 2018; Marengo and Montag 2020).

Personality remains the primary psychological construct used in psychological research to explain and predict individual behavior in a way that is stable and transferable across varying contexts (Corr and Matthews 2020). Various measures of personality traits have been shown to have predictive relations to a variety of important life outcomes at individual, interpersonal and social levels (Ozer and Benet-Martinez 2006; Hampson 2011). While there have been many previous attempts to forego the standard method of direct interviews and questionnaires, and assess personality traits instead using indirect data, for instance, patterns of word use in text samples (Fast and Funder 2008), or even observers' impressions of the physical space inhabited by an individual (Gosling et al. 2002), the newfound use of digital trace data for the purpose of personality assessment has turbocharged research and commercial interest in psychographics (Montag and Elhai 2019). Kosinski et al. (2013) used Facebook Likes to predict a variety of personal attributes including political views and personality traits. Youyou et al. (2015) showed that computational judgement of a user's personality traits based on Facebook Likes had a higher accuracy than that made by friends and family members of the user. Recently, Stachl et al. (2020) used sensor and log data harvested from smartphones and found that data classified under communication behavior, app usage and temporal patterns of activity was the most informative for prediction of personality traits (see Sariyska and Montag 2019 for an overview). Other studies have found that personality can be predicted from language used in social media (Park et al. 2015), music preferences (Rentfrow and Gosling 2003), spending records (Gladstone et al. 2019), contents of personal websites (Marcus et al. 2006) and blogs (Yarkoni 2010).

Additionally, as much of digital trace data is recorded or posted in real time, often contains personal expression and has high ecological validity, it is also highly suitable to study and predict psychological states such as moods and emotions. Bollen et al. (2011) used sentiment analysis of text content of daily Twitter feeds as a measure of public mood and used it to predict the daily changes in the closing values of the Dow Jones Industrial Average. Choudhury et al. (2013) used twitter data to identify the onset of major depression. Others have predicted emotional states from sound and physiological sensor data (AlHanai and Ghassemi 2017), smartphone data (LiKamWa et al. 2013) and typing dynamics (Cao et al. 2017).

10.4 Profiling in Politics

A standard feature found across different political systems is that different individuals react differently to the same set of political ideas and socio-economic policies. A core objective for political science thus has been to understand the factors that underlie this variance. Historically, this has been theorized to originate in personal conscious choices and processes of socialization (influence of family, religion, media, education etc.). However, assumptions of impersonal rationality and environmental determinism in politics and policy making, as much of economic sciences have found, are far from optimal (Alford et al. 2008). Starting from the work of Adorno et al. (1950) who examined right-wing political ideology in terms of personality traits, a long and diverse body of evidence has advanced the notion that political affinity can be thought of as a phenotype (Alford et al. 2008) and is, at least partially, a hardwired individual characteristic that can be linked to genetic, neurobiological, personality, and of late, even digital markers (Schreiber et al. 2013; Lewis and Bates 2014). It should be noted that research on political aspects of individual differences has examined not only party affiliation but a number of other political measures such as political attitudes, beliefs, ideology, and identification. We use the term political affinity here as an umbrella term to encompass these different measures. We discuss below whether individual political affinity can indeed be seen as a stable phenotype and whether it can be profiled with digital trace data.

Political phenotyping and psychological markers. A large, growing body of theory and research into psychological aspects of political affinity finds that it can at least partially be seen as an individual characteristic rooted in stable, individual differences in core personality traits. As Adorno et al. (1950, p. 176) noted, "The individual's pattern of thought, whatever its content, reflects his personality and is not merely an aggregate of opinions picked up helter-skelter from the ideological environment." Much of the political research examining dispositional personality traits has utilized the Big-Five framework (Gerber et al. 2011), which is the dominant framework in psychological research and is known to have predictive power in a wide array of domains ranging from psychopathology to performance in economic games (Ozer and Benet-Martinez 2006). Two of the Big-Five personality dimensions have been consistently found to be associated with measures of political orientation (Carney et al. 2008). One, higher scores on Openness to Experience (curious and inventive in contrast to cautious and consistent) have been linked to liberalism. Two, higher scores on Conscientiousness (organized and disciplined in contrast to spontaneous and careless) have been linked to conservatism (see Gerber et al. 2011 for an overview). Rentfrow et al. (2009) even replicated these findings at a macro level of analysis—state-wide mean levels of openness and conscientiousness were found to predict the percentage of votes for Democratic and Republican candidates.

Block and Block (2006) found, in a longitudinal study, that many of the personality differences noted among pre-school children, who would later grow up to be relatively liberal or conservative as young adults, were already present along the aforementioned lines. Two other factors, Extraversion and Agreeableness, while not linked to the direction of partisanship, have been shown to predict the strength of partisan identification (Gerber et al. 2012). To summarize, research across a wide variety of social and political contexts shows that dispositional personality traits underlie and have predictive power over individual political affinity towards ideological differences between the left and right.

Political phenotyping and biological markers. Studies in genetics have shown that large proportions of variance in ideologies, attitudes and other political traits can be explained by heritable genetic factors (See Hatemi and McDermott 2012 for an overview). As Hatemi and McDermott (2016) put it, "[From a bio-political perspective] Political attitudes are genetically instantiated and biologically manifested, making them physical properties of the human organism." The newly buoyant field of political neuroscience has provided further evidence that differences in political attitudes are partially derived from individual differences in neurobiological predispositions and, in turn, neural and cognitive measures can be used as predictors of political outcomes. For instance, the liberal-conservative divide and its various facets have been associated with the strength of conflict-related activity in the anterior cingulate cortex as the participants performed a conflict-monitoring task (Amodio et al. 2007), gray matter volume in the amygdala (Nam et al. 2018), and physiological response to threatening stimuli (Oxley et al. 2008) among others. Schreiber et al. (2013) found different brain activation patterns in Republicans and Democrats when playing risk-taking games. Their model, based on these brain activation patterns, was found to have significantly more predictive power for partisanship than the standard political science model based on parental socialization of party identification.

Political phenotyping and digital markers. Recently, in step with the coming of age of computational social science, many researchers have used digital trace data as a 'social sensor' to measure and predict political features. Conover et al. (2011) used Twitter data in the run-up to the 2010 U.S. midterm elections to predict the users' political alignment. In their study, a support vector machine trained on hashtag metadata predicted political affiliations with 91% accuracy. Political affiliation was also among the personal attributes that the previously mentioned study of Kosinski et al. (2013) was able to predict from Facebook Likes data. Recently, Kosinski (2021) used a facial recognition algorithm and naturalistic images of liberals and conservatives to train a model that was claimed to be able to classify liberal-conservative face-pairs with 72% accuracy. The accuracy remained high across countries, and when controlled for age, gender and ethnicity. Kristensen et al. (2017) show that parsimonious measures that use a bevy of few but selective digital traces (e.g. liking a politician's public Facebook post) can predict voter intention. Shahrezaye et al. (2019) were able to deduce political orientation from Twitter Friends-of-Friends-Networks using label propagation algorithms. Papakyriakopoulos et al. (2018) went a step further and were able to identify not only voters who might make good targets for a microtargeting campaign (politically engaged but undecided in terms of political affiliation) but also the topics they were most likely to be engaged by. It is thus becoming increasingly clear that various facets of individual political affinities can be predicted based on digital trace data. This predictive power has in turn enabled many action-possibilities, or claims thereof, in real world politics.

10.5 Action Affordances of Digital Trace Data: Microtargeting and Personalized Persuasion

The primary purpose in advertising, where psychographic profiling got its start, is mass persuasion—whether it is for the benefit of a consumer product, a political campaign or health communication. Persuasive communication has long borrowed from psychological research to come up with new strategies and improve its efficacy (Petty and Cacioppo 1996; Cialdini 2006; Baumeister et al. 2019a, b). Message tailoring, for instance, involves adjusting a message in accordance with the subject's personal interests and concerns. It is known that some recipients respond more to gain-framed messages (framed as benefits of engaging in a specific activity) and others to loss-framed messages (framed as costs of failing to engage), and the effectiveness of the message depends, in part, on individual aspects of the recipient being targeted (Lee and Aaker 2004; Mann et al. 2004). When the message framing matches the recipient's motivational orientation, the message is evaluated more positively, whether it is for anti-smoking campaigns (Kim 2006), or promotion of dental flossing (Sherman et al. 2006). Moon (2002) and Hirsh et al. (2012)

extended message tailoring research to include the recipients' personality profiles and found that it improved the efficacy of communication. Moon (2002) showed that computer-generated advice when tailored for recipients' personality increased the likelihood of change of opinion in response to the advice. However, having to assess recipient personality through detailed questionnaires limited the real-world applications of the research.

Hauser et al. (2009) were the first to employ digital trace data (clickstream data, in this case) to automatically infer the cognitive styles of individual users, in order to personalize a website's 'look and feel' in real time and found significant increase in purchase intentions. In a striking demonstration of psychographic mass persuasion that followed, Matz et al. (2017) first employed mass personality profiling based on social media data (Facebook Likes, in this case), and then tailored the content of their message (product advertisements) to the user personality traits thus inferred. They found that messages that were matched to a user's personality profiles resulted in more clicks and more purchases (although the base rate of sold products was low) when compared to the mismatched ones (see Appel and Matz 2021 for an overview).

10.6 Microtargeting and Personalized Persuasion in Politics

The principle underlying personalized persuasion—individuals respond differently to different aspects of a message, and a message can be made more persuasive by making it congruent with individual preferences or biases—is applicable to the political realm as well. Traditional research in political psychology has analyzed the association of core personality traits with the success rate of various forms of political communication and aspects of voter choice. For instance, in their study on the effects of persuasive appeals on political participation, Gerber et al. (2013) found that participants with high scores on Openness to Experience were broadly more persuadable in their responses to get-out-the-vote appeals, while other personality traits shaped responses to other specific types of messages. Gastil et al. (2008) found that when groups have members who are more Extraverted and Conscientious, it is difficult for a discussion to result in a change of attitude of the group. Work by Caprara and colleagues (2002; 2004), has focused on voter choice and the perceived personality traits of the politicians themselves and has shown, for instance, that people tend to be more favorable towards politicians whose perceived traits match their own. They proposed a model that outlines the effects of interacting congruencies between self-reported traits (and values) of voters, perceived and self-reported traits of politicians, and the ideology of the preferred political party.

However, despite the political importance attached to it and its prominence in news media, research examining the effectiveness of personalized persuasive communication in the realm of politics remains relatively scarce. Endres (2020) studied official contact records from the 2012 presidential campaign of the Republican candidate—Mitt Romney, and found that targeting Democratic voters with issue-congruent messages (where they and the Romney campaign shared common ground) increased support for Romney. Zarouali et al. (2020) showed evidence for the effectiveness of personalized persuasive communication on political attitudes and voting intentions—citizens were more strongly persuaded by political ads that matched their own personality traits.

Academic research on this subject is hampered by many factors. Chief among them are ethical considerations and data accessibility. Firstly, systematic manipulation of user behavior is, by its very nature, a controversial subject and is often prohibited by ethical requirements in many universities. Secondly, it remains to be established whether large scale social media experiments can ever attain meaningful consent from users. Thirdly, researchers are also hampered by a range of restrictions imposed by social media platforms (Hegelich 2020; Montag et al. 2021).

The few relevant large-scale experiments on large scale social media manipulation have come mostly from researchers working in association with the social media platforms themselves and have proven ethically controversial because of the manipulative nature of the experimental paradigm involved. For instance, Kramer et al. (2014), in a massive (N = 689,003) experiment on Facebook, showed that emotional states can be transferred to others via emotional contagion, and people can be manipulated into experiencing certain emotions without their consent (Verma 2014) or awareness.

In another massive experiment (N = 61,279,316), this time on political mobilization, Bond et al. (2012) found that a personalized Facebook message with an 'I voted' button sent out during the 2010 US congressional elections influenced the voting behavior of millions of people. Users who saw a personalized social message (it included pictures of a user's other friends who had voted) were 0.39% more likely to vote compared to users who only saw an informational message. They estimated that their manipulation mobilized 60,000 voters, and, combined with the ripple effect on their social graphs, ultimately led to about 340,000 additional voters to cast their votes. It is easy to miss how such efforts, ostensibly aimed at getting more people to vote, can be a form of political manipulation. Facebook has more young and female users (Auxier and Anderson 2021), and both of these demographics are more likely to be liberal. Even if Facebook randomized the distribution of messages, its manipulation is likely to have sent more liberal than conservative users to the polling booth. Given that most elections in first-past-the-post electoral systems are often decided by hair thin margins (Bush versus Gore 2000 U.S. election was decided by a mere 537 votes; Joe Biden won the crucial swing states in the 2020 elections by less than 45,000 votes), any effect of this size presents a significant political manipulation. Zittrain (2014) called it an example of 'digital gerrymandering' and cautioned against its abuse. Facebook could, for instance, use its data on users to predict political views and party affiliation and then choose to show the personalized social message and the 'I Voted' button only to the voters of a party that its corporate board prefers. There's little to doubt the plausibility of such a scenario except trust in Facebook's corporate governance. More worryingly, if such a scenario were to come to pass, it would be very difficult for media monitors or researchers to even detect it.

Support for effectiveness of personalized persuasion in politics can also be gleaned indirectly from the vote-with-your-wallet evidence deduced from the massive amount of resources being dedicated to it on the ground—political campaigns and governments spent half a billion dollars on 'psychological operations and public opinion manipulation over social media as estimated by Bradshaw and Howard (2018). We detail below some other real-world applications and effects of digital trace data in the political realm.

Digital Political Campaigns. The Obama Presidential campaigns in 2008 and 2012 saw the first high profile large-scale use of personal data and tech platforms (Bimber 2014). In 2012, both Obama and Romney campaigns and their affiliated groups were reported to have bought voter's personal data and services from private companies like Acxiom and Equifax (Duhigg 2012). They also gathered their own data through browser cookies that tracked users across the web and asked their supporters to provide access to their social media profiles, which allowed them to gather data on other people in their friend lists as well. In September 2012, Evidon, a web tracking monitoring company, discovered 76 different tracking programs on barackobama.com (Singer and Duhigg 2012). Soon after, the use of digital trace data to target voters became a standard element of political campaigns in much of the world. Research by Tactical Tech, an international technology focused NGO, identified an established ecosystem with over 250 private companies trading in digital and data-driven technologies for political influence across the political spectrum (Tactical Tech 2021).

What brought public and media scrutiny to these practices was the revelations about a British company, Cambridge Analytica, which claimed, with unbridled bombast, a capacity to swing elections by the use of personalized persuasion and behavioral microtargeting techniques based on personality profiles. They claimed having such profiles on up to 240 million Americans with 4000–5000 data points on each (BBC News 2019). The company itself acquired the data from a Cambridge University researcher—Dr. Alexander Kogan who harvested it, in turn, from Facebook using an app called 'thisisyourdigitallife'. Even as only 270,000 users directly consented to the use of their data, the app harvested data from other people in those user's friend lists leading to a data trove of 87 million profiles. The company then used its data and services and models based on that data for the campaign of Ted Cruz's Republican Presidential nomination campaign and later the 2016 Trump presidential campaign (Bakir 2020). A subsequent document leak revealed that Cambridge Analytica's political data operations stretched to 68 countries (Cadwalladr 2020).

It is worth noting that since political affinities are perceived to be fairly stable over time, once estimates of political affinities have been gained for a high number of identifiable voters, they can be used for long periods of time. Indeed, failed political campaigns have been reported to have sold voter data they collected to other candidates and even private firms for subsequent campaigns (Pagliery 2016). Even if these estimates and claims by campaigns and political consultancies were not to be reliable, another process, described by Hersh (2015) as the "perceived voter model", comes into effect—as soon as political campaigns believe that they have access to voter information, they come to view voters and design their outreach through the lens of that data (even if that perception were to be misleading).

Door-to-door Canvassing. While much of the debate around the aforementioned concerns stays restricted to the digital world, there are clear ramifications for real life in-person political interactions. Consider, for instance, a political activist campaigning for a candidate by knocking on physical doors and talking to voters in person, a practice as old as democracy itself and termed canvassing. Digital trace data could be (and in several forms already is; Duhigg 2012) used to access detailed demographic and psychographic information on an individually identifiable voter, and principles gleaned from behavioral sciences could be used to generate a script of talking points tailored for the preferences and biases of that particular voter, all before the voter answers the knock on her door. The 2012 Obama and Romney campaigns were reported to have planned to use detailed digital trace data bought from private data companies to generate scripts and selective call lists for telephone canvassing (Duhigg 2012). In Germany, the conservative party (CDU) has started using a campaigning app, Connect 17, that allows campaigners to record their impression of the reactions of the inhabitants of an address that they have canvassed. The app also functions as an organizational tool: the campaign office can guide field campaigners to special addresses (Essif 2017). If combined with psychological profiling, both the messaging and the person ringing at the door could be chosen to fit the preferences of the voter.

Gerrymandering. Gerrymandering represents another new arena for the use of digital trace data for political manipulation. It is not unusual for support and opposition for a particular political entity to vary geographically over neighborhoods, villages, blocks etc. Especially, in first-past-the-post electoral systems, the way such subunits/precincts are chosen to define a single electoral district (called redistricting, done periodically with the updating of the census data) can confer advantage to particular political entities. In some democracies, such redistricting is carried out by independent election commissions (e.g., India, Australia, UK) and is uncontroversial. But in others it is carried out by legislative bodies (e.g., USA, France) and is often used by the incumbent parties to confer unfair advantages to themselves in a practice termed as gerrymandering (after the US politician Elbridge Gerry and his carving of a Boston constituency in 1812 in the shape of a Salamander). Gerrymandering allows politicians to pick among specific combinations of blocs of voters that will get to vote for a particular constituency.

As pernicious as gerrymandering had always been, until recently, well into the digital era, it had been a fairly crude process restricted to the level of a precinct at which aggregated official political data was publicly available. Now, easy availability of consumer, social media and other personal data has thrown gerrymandering into a higher gear—partisan mapmakers can now work out with surprising accuracy the political leanings and voting likelihoods of individual voters, bin them into households and blocks, and in turn draw district lines that have been fine-tuned at the smallest possible level. The increasing granularity in US Gerrymandering has been clear for a while. For example, in the maps drawn by the 2011 North Carolina legislature, residents of one-and-a-half blocks of a small neighborhood street received three different ballot styles for the 2012 general election (Dickson v. Rucho 2019; Newkirk 2017). In another, 18 different sets of ballots had to be printed for a single election cycle. In Virginia, the 2011 maps tripled the previous number of split precincts. The effects of such hyper-gerrymandering on electoral fortunes have also been made apparent. Stephanopoulos and McGhee (2015), for instance, devised a metric called the efficiency gap, which measures whether either party enjoyed a systematic advantage in turning votes into seats based on the number of votes each party wastes in an election. They found, for instance, in the case of Wisconsin, double-digit statewide efficiency gaps in favor of Republicans in each election cycle since the 2010 redistricting by the Republican legislature. Further voter-level psychological and political insights and yet more data gleaned since 2010 are only expected to worsen the problem in the redistricting cycle that would follow the 2020 census.

Affective Manipulation. In addition to personalized targeting based on demographics or psychological traits, people can also be targeted based on affective psychological states like moods and emotions. Affective profiling is based on the fact that much of digital trace data is recorded or posted in real time, often contains personal expression and has high ecological validity. According to *The Australian*'s reporting on a leaked confidential document prepared by Facebook Australia (The Australian 2017), Facebook used its data on 6.4 million young Facebook users from Australia and New Zealand that included 1.9 million high school students, including some as young as 14, for research aimed at mining for psychological and behavioral insights. It then offered advertisers the possibility to target teenagers when they were psychologically vulnerable, such as when they felt "worthless," "insecure," "stressed," "defeated," "anxious," and like a "failure" and underscored Facebook's capacity to target ads to "moments when young people need a confidence boost" as a unique selling point. The report also claimed that Facebook had been monitoring user activity in real time to track their emotional ebb and flow. While, in this instance, this capacity was offered to non-political advertisers, it does offer a window into corporate research on psychological state-based affective manipulation, which otherwise happens behind closed doors and its potential applications to politics are but one step removed.

10.7 Limitations

Even as digital data and analytical tools are expected to only become more prominent in the time to come, there are many natural limitations to their influence in real world politics. Individual choices, which might indeed have a predictable and manipulatable component, are not, for the most part, deterministic. And the influence of environmental socialization is likely to remain the dominant factor in individual political decisions. Additionally, political propaganda and persuasion are an old art form and have long had a range of non-data tools under their belt, that are both proven and less expensive (Bakir et al. 2019). Democratic systems have been able to adapt to them and thrive in spite of them. It is the fact that modern politics, especially the first-past-the-post electoral system, often relies on hair thin margins, which makes it susceptible to any external factor that can be used to marginally alter the probability function of voting behavior (of which, modern effects like personalized persuasion and misinformation are but two among many tools in the arsenal of political manipulation).

It should also be noted that the data gathered from personal digital traces and analytical models derived from such data are not static. Several factors might limit the prediction and action affordances of a particular set of data or predictive model. For example, while political affinities might be consistent over time, the digital clues to predict them might not be. The aforementioned Kosinski (2021) study, for instance, takes pictures from Facebook and dating sites. Because the classification of political orientation is done with a black box algorithm (a convolutional neural network with 50 layers based on the ResNet-50 architecture), it is not clear what the algorithm really learns and what signals the automated classification is based on. Consequently, it is also not clear how stable over time these hidden features, that underpin the classification accuracy, are likely to be. For instance, if these hidden signals were theoretically to be nuances in the coloring or lighting of pictures because liberals and conservatives use different smartphones with different cameras, the accuracy of these predictions might then vary with new versions of hardware cameras or with new photo filters that come to be widely used. Additionally, though it might be true in some cases, it is a general misunderstanding that, when it comes to big data, more is always better. Adding variables to a data analysis that do not carry any meaningful signal tend to increase the variance of the independent variables. This will lead to an increase in accuracy on test data but decrease in accuracy on new data. This phenomenon is known as the ‘curse of dimensionality’ (James et al. 2013) and prevents the useful combination of more and more personal data.

10.8 General Discussion

Though its antecedents are often ignored, behavioral emphasis in political science has been nearly a century in the making. When behavioralism first emerged in the 1930s in the United States, it attempted to shift the study of politics from its emphasis on historical narratives, political theory, institutions and legal mechanisms towards a more objective, quantified approach as a social science that emphasized behavior and actions of individuals and political groupings. Developing in tandem with the rise of behavioral sciences in general, it adopted empirical methods, modelled after similar turns in other social sciences, especially psychology and sociology (Easton 1953). However, from the very start, it came under heavy criticism from within political science (Dahl 1961) and also from the critical theorists of the Frankfurt school (Adorno 1976; Held 1980). Critical theorists bundled behavioralist approaches in politics among others that they criticized under the label of positivism. They held that when the subject of an investigation is subjective (such as opinions, attitudes or personality), quantitative methods yield statements about the subjective only in the methodological sense. Instead of being directed towards knowledge as a goal, they are directed towards knowledge strictly as quantifiable knowledge occluding the possibilities of what cannot be quantified (Adorno 1976), thereby serving to turn matters of value judgment into instrumental problems of efficiency and utility (Gorton 2016). Others found behavioralism's insistence on being 'value-neutral' as denying the very possibility of political philosophy (Beehler and Drengson 1978), and yet others criticized its focus on explanations of the-way-things-are as pro status quo and inherently conservative (Dahl 1961).

Despite the variety and volume of such criticism, the chief failure of early behavioralism in political sciences turned out to be the fact that it didn't work, and failed to find any law-like generalizations about political behavior that had operational predictive power. The research detailed in this article shows that twenty-first century behavioralism in its new avatar as computational politics or political data science looks set to overturn its earlier failures, both in prediction and profiling of individuals in terms of their political phenotypes, and in manipulation of their opinions. Early criticism, of behavioralism in political science and positivism in general, is hence worth revisiting as much of it remains relevant to current research and developments in these fields (Gorton 2016).

This article has strived to point out a broad new toolkit arising from a convergence of data science with a slew of subfields within behavioral sciences—digital phenotyping, mobile sensing, political data science on one hand and political psychology, marketing research and behavioral economics on the other—that seem to be offering a way 'from outside in' and can be purposed for manipulation and coercion at the individual level. Personal digital trace data, available in nearly inexhaustible quantities, especially to the big platforms themselves, when coupled with advances in behavioral sciences can be compiled into a comprehensive model of an individual's daily life, routines, traits and even mental health; its usage and reach often unbeknownst to the individual herself. The ostensible rationale for much of this research is generation of knowledge that might then benefit a technocratic elite to improve the functioning of our political (and, in the context of this volume, our health) systems. Indeed, engineers and analysts engaged in political targeting for the Obama 2012 campaign were initially lauded in much of left-leaning media with headlines like 'When the Nerds Go Marching In' (Madrigal 2012) and 'Data You Can Believe In' (Rutenberg 2013). However, this techno-optimism soon gave way to the reality that similar strategies were used in the Trump 2016 and the Brexit-Leave campaign, and these techniques came to be seen in media and public eyes as an assault on democracy. It is now clear that knowledge generated within fields like psychoinformatics, and political data science and meant for benevolent academic purposes can come to be seized by political consultants and repurposed for profiling and manipulating voters. Consider, for example, the finding by Caprara and colleagues (2002; 2004) that voters prefer politicians who they perceive to have the same personality traits as they do. A hitherto unexamined paradigm of manipulation enters the picture when a politician can access models derived from personal data to infer voters' personalities and present a congruent personality to each voter. In the 2016 US presidential election, the digital campaign manager for the Trump campaign claimed that his team tested around 50,000–60,000 advertisement variations a day using Facebook's tool, Dynamic Creative, to find optimal combinations based on engagement metrics

(Bartlett et al. 2018, p. 33). These possibilities do not fit into the old paradigms of campaign monitoring and, in most countries, there are few, if any, barriers to their unrestricted use.

Lastly, one would be remiss not to recount in this context that optimal functioning of democratic politics is especially sensitive to developments that undermine individual autonomy since democracies derive not only their legitimacy but also their efficacy from individual citizens making independent decisions without interference or coercion (Landemore 2017). The heart of liberal democracies lies in a distributed, collective intelligence derived ultimately from the summation of millions of independent individual voices. It's this independence of individual opinions that enshrines plurality of thought into every facet of democratic societies, and fuels not only our defense against authoritarianism, but also our capacity to innovate and flexibly adapt in the face of complex challenges. However, this independence presupposes informational self-determination and an environment free from personalized targeting and coercion. Already under assault from hyper-partisan media coverage and misinformation, a contemporary citizen forming her opinion must also now confront intrusions by psychological targeting fueled by her own personal data. For our society at large, there is a risk that political actors, whether they are public, private or foreign, gaining the capacity to look *from outside in* would undermine this independence and with that the basis of our collective intelligence.

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Chapter 11
A Practical Guide to WhatsApp Data in Social Science Research

Julian Kohne, Jon D. Elhai, and Christian Montag

In this chapter, we will first give a brief overview of the mobile instant messaging landscape. Subsequently, we focus on the instant messaging application "WhatsApp" and describe its current features and which kinds of data can be extracted from it. Based on the existing literature, we provide practical advice for researchers seeking to work with WhatsApp data with respect to data collection, participant incentivization, data processing, informed consent, anonymization, and reproducibility of research. These insights might also prove useful to researchers seeking to work with other kinds of chat log data. We conclude that WhatsApp is an intriguing data source for social science research questions but that the data have to be treated with great caution to ensure ethical conduct. To facilitate this, we present several issues to contemplate for designing studies and briefly introduce the "WhatsR" package for R—our own package for parsing and visualizing data from exported WhatsApp chat logs with convenience features for tailoring, anonymizing, and extracting metadata from them.

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_11

11.1 Mobile Instant Messaging and WhatsApp

Digital methods for interpersonal communication have fundamentally altered the way we connect with other people over the past decades. Starting with email in the 1970s, digital communication became increasingly important across all areas of life while its technology kept constantly evolving. In the late 1990s and early 2000s, standalone **instant messengers (IM)** such as ICQ, MSN Messenger, or AOL Instant Messenger (AIM) quickly became popular (Desjardins 2016). From the mid 2000s to the early 2010s, the supremacy of these instant messengers was challenged by emerging social media platforms. Websites such as MySpace and Facebook offered users options to design their own profiles with personal information, photos, videos and the ability to create permanent posts on their or their friends' profiles. In addition, Facebook and MySpace quickly integrated their own **social media instant messenger** clients into their platforms, allowing users to also exchange private messages. Digital communication was reshaped again by the emergence of smartphones in the late 2000s and early 2010s. While SMS still had the advantage of mobility over instant messaging until this point, the launch of **mobile instant messaging (MIM)** apps made SMS largely redundant (Shandrow 2014; Thurlow and Poff 2013). These apps combined the advantages of instant messaging with the portability of SMS and quickly replaced texting for most use cases. In addition, instant messaging was perceived as more social, informal and conversational in nature than texting (Church and De Oliveira 2013).

As of today, the digital communication landscape is largely dominated by mobile instant messaging applications that can be used from any device with a web browser (cf. Jucker and Dürscheid 2012). Some of the most popular instant messaging clients are parts of social media platforms, such as the Facebook/Instagram messenger, WeChat, or Tencent QQ, while others such as WhatsApp, Telegram, or Viber are standalone applications that focus primarily on their instant messaging functions. There are regional differences regarding the popularity of different mobile instant messengers, but the market is dominated by a few international providers. Figure 11.1 provides an overview of the most popular instant messengers per country. Notably, Facebook has the largest market share worldwide through the Facebook/Instagram messenger and WhatsApp (Olson 2014). In 2021, WhatsApp is the most popular mobile instant messenger in the majority of countries around the globe (Kemp 2020) with approximately 2 billion monthly active users worldwide (Clement 2020). It is currently available for free as a smartphone app for iOS (iOS 9 or newer), Android (version 4.0.3 or newer), selected KaiOS devices, and also offers free desktop clients and a mobile web version. It does not require users to set up an account with an email address or username and instead relies on users' phone numbers as identification. As such, WhatsApp cannot be used without a phone number but is easy to set up for anyone who has a mobile phone. For an overview of the most popular mobile instant messengers by number of monthly active users, see Table 11.1.

Due to its extremely large user base, its worldwide popularity, diverse features, possibility to export chat logs, and its highly frequent usage by most users (Montag

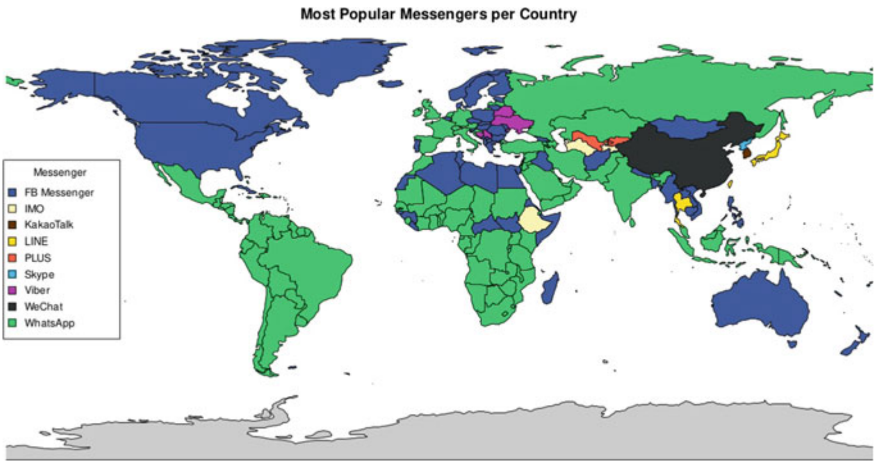


Fig. 11.1 Most popular instant messaging applications per country. Data were recreated from Kemp (2020)

et al. 2015), WhatsApp is probably the most intriguing source for mobile instant messenger data for social scientists at this moment. The service essentially logs interpersonal interactions passively while the application is being used and can thus provide a detailed report of a fraction of all interactions that connect two or more people. Data from WhatsApp provide high resolution interactional data, require little effort on the side of study participants, can be collected retrospectively from a natural setting, and objectively quantify behavior in interpersonal interactions. Consequently, WhatsApp data have been used to investigate diverse research questions in linguistics (Verheijen and Stoop 2016; Ueberwasser and Stark 2017; Dürscheid and Frick 2014), political science (Resende et al. 2019a; Narayanan et al. 2019; Garimella and Tyson 2018), education (Costa-Sánchez and Guerrero-Pico 2020; Rosenberg and Asterhan 2018), and research about social relationships (Aharony 2015; Garcıa-Gómez 2018). However, despite their potential, data from WhatsApp are a methodical and technical challenge for most researchers because they require special considerations for data collection, participant incentivization, data processing, informed consent, anonymization, and reproducibility of research. In this book chapter, we draw on previous studies and the methods they employed to work with data from WhatsApp to give practical advice to researchers who seek to work with WhatsApp data themselves. These insights might also help to inform other studies that work with sensitive chat data from other providers but are tailored to WhatsApp in particular.

Table 11.1 Overview of most frequently used Instant Messengers, based on monthly active users (MAU)

Instant messenger	Active users	Features
WhatsApp	2 Billion[1]	Smartphone App and browser-based client for private instant messaging
Facebook messenger	1.8 Billion[a]	Smartphone app and browser-based client for private instant messaging for users of Facebook and Instagram
WeChat	1.2 Billion[2]	Multi-purpose app for instant messaging, mobile payment, and public social network accounts
Tencent QQ	650 Million[a]	Web portal for gaming, music, microblogging, shopping, and instant messaging
Snapchat	430 Million[a]	Multimedia messaging app with a primary focus on photos and messages that are automatically deleted after being viewed
Telegram	400 Million[3]	Open source smartphone app and browser based client for private instant messaging with a focus on open source and encryption
Skype	300 Million[4]	Cross-platform service for video and conference calls that also includes instant messaging features
Viber	260 Million[5]	Smartphone app and desktop client for cross-platform voice calls and instant messaging
Discord	250 Million[6]	Mobile app and desktop client for cross-platform voice and video calling and instant messaging. Primarily designed for online gamers
iMessage	1.3 Billion[7]	Exclusive service for private instant messaging between Apple devices. User number reflects the total number of Apple devices with the service installed, as opposed to monthly active users for the other applications

Data on number of users were collected from multiple sources and range across multiple years (2017–2020). The table should thus be regarded as an approximate overview rather than a factual ranking
[a]https://www.statista.com/statistics/258749/most-popular-global-mobile-messenger-apps/

11.2 Current Features of WhatsApp

Since launch, the range of features in WhatsApp has constantly expanded, with a focus on cross-platform interaction, multimedia content, live streaming capabilities,

[1] https://www.statista.com/statistics/260819/number-of-monthly-active-whatsapp-users/.

[2] https://www.businessofapps.com/data/wechat-statistics/.

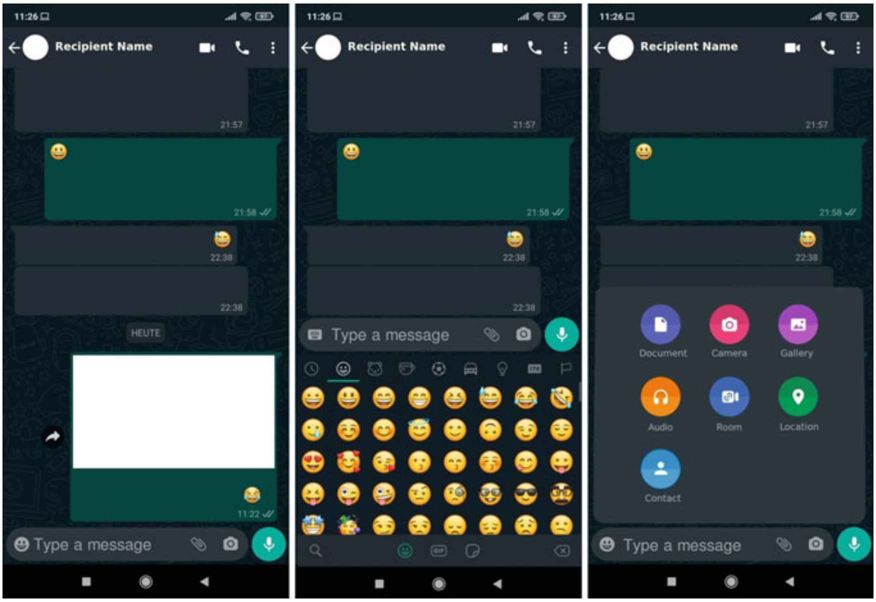
[3] https://techcrunch.com/2020/04/24/telegram-hits-400-million-monthly-active-users/.

[4] https://azure.microsoft.com/en-us/blog/how-skype-modernized-its-backend-infrastructure.

[5] https://99firms.com/blog/viber-statistics/.

[6] https://www.messengerpeople.com/global-messenger-usage-statistics/ [h]https://247wallst.com/technology-3/2019/01/17/apple-facebook-messaging/.

[7] https://247wallst.com/technology-3/2019/01/17/apple-facebook-messaging/



(a) WhatsApp Chat (b) Emoji Menu (c) Attachments Menu

Fig. 11.2 Anonymized screenshots showcasing the WhatsApp user interface. Clicking on the emoji symbol on the bottom left in (**a**) opens the emoji menu in (**b**). From the emoji menu, users can select emoji, GIFs and stickers to send. Clicking on the paperclip symbol on the bottom right in (**a**) opens the file attachment menu shown in (**c**). From this menu, users can browse their phone or open their camera to send different kinds of file attachments. The camera symbol on the bottom right in (**a**) allows users to record pictures or videos to send as files and the microphone button enables users to send voice messages. Video and voice calls can be started with the camera and phone receiver symbol on the top right in (**a**) respectively

and group chats. WhatsApp is free to use for private users but offers a premium business version to monetize its market share. The messenger has become more secure and private over time, but concerns remain among many users regarding privacy and data sharing with Facebook and Instagram (e.g. Sindermann et al. 2021. These concerns motivated millions of users to switch to Signal or Telegram in early 2021 (Hern 2021a), when WhatsApp updated its privacy policy and planned to discontinue service to users who do not accept the updated policy. The impact of this reaction was so pronounced that WhatsApp delayed the update and started an information campaign to convince users that the content of private messages will not be shared with third parties (Hern 2021b). As of writing this book chapter, WhatsApp supports user profiles, status messages, and multimedia instant messaging. To highlight the opportunities for conducting social science research with WhatsApp data, we discuss its current features, and thus the kinds of data that WhatsApp generates, in the following paragraphs.

11.2.1 User Profiles

WhatsApp allows users to set up rudimentary user profiles with a customizable username, profile picture, and a short textual infobox. Usernames are limited to 25 characters or emoji. For the infobox, users can chose from a list of preselected options (e.g. "busy" or "at work"), or create custom text with a maximum of 139 characters or emoji. To see the infobox, one has to actively open the respective user profile by clicking on the profile picture or the entry in the WhatsApp contact list. Profile pictures can either be uploaded from the phone's gallery or taken directly by accessing the phone's cameras. The profile picture will be displayed to chat partners in the respective chat, in their contact list, and in their chat overview. Importantly, users will not be displayed on others' phones with their self-selected usernames, but with the name they were saved under in the other's contact list. The self-selected username is only displayed to people in group chats who do not have the person in their contact list. In this case, the displayed name consists of the phone number followed by a tilde (~), and the self-selected username.

11.2.2 Status Messages

WhatsApp users can create a status message that will be visible for 24 h in a separate tab to all their contacts who also have the user's number saved in their contact list. A status message can be a text message containing 700 characters or emoji with customizable background color, font, and additional GIFs. Another option is to upload an image from the phone's gallery or take one directly through the phone's cameras and customize it through filters, cropping, stickers, colored text, or free form drawings. By opening the status of somebody else and swiping up, users can directly react to statuses and start a private chat conversation. The status feature is similar to Instagram's and Snapchat's "stories".

11.2.3 Multimedia Instant Messaging

Multimedia instant messaging is WhatsApp's core feature. Users can either chat with each other in private conversations or create and join groups with multiple members. Users can be invited to a group via the 'add participant' option or through a public invite link (or QR code) that enables people to join a group themselves. The limit for participants in a group is 256 members. WhatsApp also has a feature called 'broadcasts', that allows users to define their own group of contacts and send them messages simultaneously. In contrast to a group chat, the recipients do not know that other people received the same message and instead receive the message in the regular private chat they have with the sender (WhatsApp FAQ 2020f). Within a private chat, users can see if their chat partner is currently online (i.e. has the app open on their screen) or is in the process of typing a message. Received messages elicit a notification and/or pop-message on the recipient's phone and display the name of the sender, content of the message and the time the message was received. By tapping on a message within a chat, a menu opens that allows users to directly answer the message, forward the message to other contacts, highlight the message with a 'star' to save it in a separate log, copy the message text, or delete the message. Sent messages can be deleted for all participants for up to one hour after they have been sent. Afterwards, the message can only be deleted on the device of the sender but not from devices of the recipients (WhatsApp FAQ 2020c). Chats can also be configured so that all messages are automatically deleted after seven days (Haselton 2020).

Text. Users of WhatsApp can send each other text messages of up to 65,536 characters per message. The message is transferred instantly when both users have an active internet connection or is otherwise sent and received as soon as an internet connection is reestablished. Text can be formatted as **bold**, *italics*, ~~strikethrough~~ or monospaced by encasing text in specified formatting sequences (WhatsApp FAQ, 2020d). When links are copied into a message, they are automatically formatted to be clickable, and the message is appended with an automatically generated preview of the website's content. Text can also be used to create emoticons—e.g. ':-)' —that are different from emoji (see below).

Emoji. Besides regular text characters, users can also include emoji in their text messages. Emoji can be accessed through a small icon on the left side of the message entry field and are ordered in nine categories. In the first category, WhatsApp suggests the most frequently and most recently used emoji, the second category includes emoji of 'Smilies & People' and the subsequent categories contain emoji of 'Animals & Nature', 'Food & Drink', 'Activity', 'Travel & Places', 'Objects', 'Symbols' and 'Flags'. For most emoji containing faces or bodyparts, users can select a default skintone variant ranging from 'light skin' to'dark skin' in six different categories, selectable for each individual emoji. Including all skintone variants, there are 3229 unique emoji in WhatsApp to date, but new emoji are regularly added. Crucially, WhatsApp has their own renderings of emoji so that they look identical on the phone of the sender and recipient, even if they are using different operating systems (cf. Miller et al. 2016). If an emoji is sent on its own without accompanying text, an enlarged version of the emoji is sent to the recipient.

GIFs. In the same menu that grants access to emoji, there is another tab that allows users to send each other GIFs. These are short, looped video clips that can be selected from a list of globally popular ones or can be queried by keywords. The GIFs are provided by GIPHY,[8] another subsidiary company of Facebook. GIFs can be prepended to a regular message containing text or emoji or can be sent individually. Recipients must click on the GIF to play back the videoclip.

[8] https://giphy.com/

Stickers. The third and last option in the emoji menu is to send stickers. Stickers are comparably large images that are designed to express specific emotions, concepts, or situations. The layout of stickers is different from sent messages or images because they do not have a bounding box and consequently blend more into the background. In contrast to emoji, stickers must be downloaded manually in the sticker menu before they can be used, and users can select from a wide variety of different sticker collections. Users can receive and correctly display stickers even if they did not download a collection as long as the sender has downloaded the respective collection. WhatsApp also allows the import of third-party stickers and even allows users to create and import their own stickers via third-party apps.

Images. One early feature of WhatsApp was the sending of images. Users can either send saved photos and images from their gallery or directly take a photo with their camera function. For sending an image from their phone's gallery, users can click on a paperclip symbol next to the text message entry field and then select 'Gallery' from the file attachments menu. For sending a photo using the phone's cameras, users can click on the camera symbol next to the paperclip symbol. Before the image is sent, users have the opportunity to crop and rotate the image, select a filter for controlling the color saturation and hue, paste colored text directly into the image, add a limited selection of emoji to the image, or add free form drawings to the image. Sent images are displayed in the chat as a square of 800 by 800 pixels but are shown in full resolution when clicked on. When more than three images are sent by the same user in quick succession without being interrupted by a message from another chat partner, or a message containing no image, they are displayed as an album instead. An album shows the first four images as 200 by 200 pixel previews and displays the remaining number of images in the album as a transparent '+ x' icon on the bottom right preview image. When clicking on an album, an image browser opens that allows users to quickly vertically scroll through all images in the album. The maximum file size for individual photos or images is 16mb (WhatsApp FAQ 2020g). In mid 2021, WhatsApp also introduced a feature that allows users to set an option for sent images and videos so that recipients can only view the media file once, and can neither forward it to others nor save it to their gallery (WhatsApp FAQ 2020e).

Audio Messages. Audio messages can be sent via WhatsApp either by clicking on the paperclip symbol in a chat and selecting the 'Audio' icon in the file attachment menu, or by pressing down on the microphone symbol on the bottom right of a chat. For the former option, users can select existing audio files on their device and send them to their chat partners up to a maximum file size of 16mb. For the latter option, users can create a live audio recording of unlimited length (Dürscheid and Frick 2014). After a live message is recorded, users can replay it again and then decide to either send the recording or delete it. For live audio messages, recipients see a message with the sender's profile picture, a playback button, the length of the audio message, and a progress bar. When they click on the playback button, the voice message is played back, and the button turns blue for the sender and recipient so that senders can also see if their voice messages have been played back. For audio files sent as file attachments, the recipient sees a message with a sent file that can be played back in the chat without notifying the sender.

Videos. Similar to the audio sending feature, WhatsApp also supports sending video files. To send a video that is saved on the device, users can open the file attachment menu by clicking on the paperclip icon next to the text message entry field and select 'Gallery'. This procedure does not only display the images and photos on the phone but also videos. To record a new video and send it to a contact, users can click on the camera symbol next to the paperclip symbol, opening the phone's camera menu. Tapping once takes a photograph/image, while holding down the shutter button records a video clip. Users can append a text message and emoji before sending the video file and edit the video file itself by adding colored text, a limited selection of stickers, or add emoji and free form drawings as an additional layer over the video. For self-recorded videos, users can select whether it should be sent as a video, or as a compressed GIF with a smaller file size. Recipients must click on an 800 by 800 pixels preview showing the first frame of the video to play it back. The maximum file size for sending videos is 16mb, corresponding to 90 to 180s of video on most modern phones (WhatsApp FAQ 2020g). Maximum sendable video length can be increased by compressing videos into GIFs or other file formats.

Locations. WhatsApp has a feature that allows users to interactively share locations with others. If users click on the paperclip icon next to the text message entry field in a chat, the file attachment menu opens and lets users select the 'Location' icon. Clicking on the icon opens another menu with a Google Maps screen displaying the current location, orientation, and points of interest that are close by. Users can share a static snapshot of their current location, a nearby point of interest, or another location. By clicking on the square icon in the top left corner of the location screen, users can search for keywords, addresses or interactively select a point on the map. When a static location is shared, recipients receive a message with a preview image from Google Maps that highlights the location with a thumbtack. By clicking on the preview, users are forwarded to a Google Maps page in their browser with the latitude and longitude coordinates of the sent location preselected. Users can also share their 'live location' by clicking on the corresponding button in the location menu. Live locations are interactively updated in real-time as the sender moves and can thus be used to facilitate meetups. By default, live locations can be shared for 15 min, one hour or eight hours, after which tracking updates will automatically stop. After live tracking has stopped, the last tracked location with its corresponding timestamp will stay accessible in the chat. When a live location is shared, recipients receive a message with a Google Maps preview of the sender's current location and are forwarded to a map tab within WhatsApp upon clicking on the preview. In this tab, recipients can share their own live location as well, and if they do, both users can interactively see each other move on the same map for the specified amount of time.

Documents. Documents can be sent via WhatsApp by clicking on the paperclip icon in a chat next to the text message entry field and subsequently clicking on the ’Documents’ icon in the file attachments menu. Supported file types are PDFs, office documents (e.g. docx, pptx or xlsx) and several other common file formats (e.g. csv, zip or html). Unlike other types of WhatsApp message attachments, the document sending feature supports file sizes of up to 100mb instead of 16mb. Text messages and emoji can be appended to documents in a menu that opens before the document is sent. Recipients see a message with a small preview of the first page of the document and can download the document to their device by clicking on it.

Contacts. Users of WhatsApp can directly share contacts with others by clicking on the paperclip icon in a chat next to the text message entry field and subsequently clicking on the ’Contact’ icon in the file attachments menu. Users can then select one or multiple contacts from a list that includes all contacts on the phone, even if the contact in question does not have WhatsApp installed. Contacts are sent as a regular vcf file. If the sent contact has WhatsApp installed, the recipient receives a message with the name that the sender has saved the contact under in their phone’s contact list and their self-selected profile picture. By clicking on the contact, the recipient opens a tab displaying the contact’s phone number and buttons to directly add the contact to their contact list or directly message, call or video call the contact in WhatsApp. If the sent contact does not have WhatsApp installed on their phone, the sent message includes a button to send an invitation to use WhatsApp and includes a blank profile picture. When the recipient clicks on such a received contact, a separate tab opens that displays the contact name, blank profile picture, phone number and a button to directly add them to their phone’s contact list. Multiple contacts can be sent at once and are then summarized into one message, displaying the name of the first sent contact and the number of additional contacts. Clicking on the summarized message opens the regular contact tab as a scrollable list with all received contacts and the applicable options described above.

Voice calls. In addition to sending each other audio messages, users can also conduct live voice calls on WhatsApp that work like regular phone calls. By clicking on the phone receiver symbol on the top right of the chat and confirming that a voice call should be started, the sender calls the receiver. A screen opens on the receiver’s phone, signaling an incoming WhatsApp voice call that can be accepted or declined. Both users can put the conversation on speaker, mute their microphone or switch to a video call by enabling their camera. Both participants of a call can add additional users who can then join the call. The limit of maximum users that can participate in a voice call has recently been upgraded from four to eight users (WhatsApp FAQ 2020b). In group chats with up to eight participants, every member of the chat can initiate a group call by clicking on the phone receiver icon in the group chat. In chats with more than eight participants, users can only select up to eight members to call when clicking on the phone receiver symbol.

Video calls. Similar to voice calls, WhatsApp also has a video call feature that allows users to conduct live calls with audio and video. A video call can be initiated in a private chat or group chat by clicking on the video camera symbol on the top right in the chat window. For group chats, the symbol is only present for chats with up to eight participants as this is the maximum number of participants for video calls (WhatsApp FAQ 2020b). Receivers can accept or decline the call and decide if they want to join with audio and video or with audio only. Once they are participating in the call, they have options to disable audio, video or drop the call at any time.

Messenger Rooms. Messenger rooms are a special kind of video call in Facebook but are accessible through WhatsApp as well. To start a messenger room, users must click on the paperclip icon in a chat and select the 'Room' icon from the file attachment menu. Senders will then be forwarded to the Facebook Messenger app if they have it installed on their phone, or to a browser tab with Facebook Messenger open. They can then create a group video call within Facebook Messenger and send an invitation link to this room directly through WhatsApp. As such, messenger rooms are not a feature of WhatsApp but a feature of the Facebook Messenger that is easily accessible through WhatsApp. Importantly, WhatsApp video calls are end-to-end encrypted, but Facebook Messenger rooms are not (WhatsApp FAQ 2020a). The creator of a Facebook Messenger room must have a Facebook account and must log in to create the room, but participants can join the room through the link without logging in to a Facebook account. An advantage of Facebook Messenger rooms over built-in WhatsApp group calls is that they can host up to 50 participants and are accessible through the invite link in a regular browser and can thus also include people who do not use WhatsApp (Messenger 2020).

Payments. WhatsApp Pay is a feature that is still being tested and is currently only available in Brazil and India (Perez 2018; Reuters 2020). Similar to a feature that has been available in WeChat for some time, users can link their account to a credit card number or bank account and directly send payments through WhatsApp to other users who have set up the feature (WhatsApp 2020). If and when this feature will become available in other countries is still unknown to the best of our knowledge.

11.3 Data Collection and Processing

In the following paragraphs, we will provide a hands-on overview for researchers who are interested in collecting and analyzing WhatsApp data. To this end, we will discuss previous approaches, their shortcomings and advantages, and will outline best practices with respect to methodological, technical, ethical, and legal challenges. The discussion explicitly focuses on WhatsApp but might also apply to other (mobile) instant messaging services. As we have highlighted in previous sections, there are many different types of WhatsApp data that can be used to investigate social science research questions. As a general distinction, we will differentiate here between **data *about* WhatsApp** and **data *from* WhatsApp**. While the former includes data that provide insights into how WhatsApp is subjectively perceived or used, the latter refers to objectively quantified behaviors of WhatsApp usage. For example, qualitative studies (e.g. O'Hara et al. 2014; Pang and Woo 2020) or surveys (e.g. Aizenkot and Kashy-Rosenbaum 2019, 2020) would represent data *about* WhatsApp, while status messages (e.g. Sánchez-Moya and Cruz-Moya 2015; Maız-Arévalo 2018), usage statistics (e.g. Montag et al. 2015) or extracted chat logs (e.g. Seufert et al. 2015; Resende et al. 2019a; Bursztyn and Birnbaum 2019) represent data *from* WhatsApp. In the following paragraphs, we will specifically focus on data *from* WhatsApp, and especially on exported chat logs.

11.3.1 Data Collection

As opposed to other social media platforms like Facebook, Twitter or Instagram, mobile instant messengers seek to enable **private communication** that is not accessible for anybody outside the chat. For this reason, WhatsApp is end-to-end encrypted, meaning that chat messages are only accessible to participants of the respective chat and cannot be obtained through cooperation with WhatsApp/Facebook or an API. While WhatsApp profile information, profile picture, self-selected username, or status messages are publicly available to everyone who saves the respective phone number in their contact list, there are only two ways of collecting WhatsApp chat logs from research participants: Joining the respective chat conversation or asking a participant of the chat conversation to donate their data for research purposes. Both methods essentially rely on the WhatsApp feature to export one's own chat log in any conversation (Whatsapp FAQ 2021) or methods to directly extract the data from the SQLite database of the phone (Garimella and Tyson 2018; Gudipaty and Jhala 2015). To use the manual export feature, users can go to any chat, tap on the three dots in the top right corner, select "more" and then click "export chat". Users can then select whether a chat should be exported including media files (e.g. sent videos or images) or without media files (only textual chat log and sent contacts are exported). The files can then be sent unencrypted to an email address or via any other data sharing application installed on the phone. Importantly, the export feature allows the export of the last 40,000 messages when selecting "export without media files" but only the last 10,000 messages when selecting "export with media files". If the latter is selected, the last couple of sent media files will be exported as additional attachments.

Joining the conversation. One way of obtaining WhatsApp chat logs is to join the respective conversation and then extract the chat logs or make screenshots yourself. This method has first been described by Garimella and Tyson (2018) and has been subsequently used for investigating public WhatsApp group chats, mainly in Brazil and South-East Asia (Narayanan et al. 2019; Machado et al. 2019; Resende et al. 2019; Resende et al. 2019; Melo et al. 2019). Basically, it involves scraping the internet for invite links to public WhatsApp groups using specified keywords, joining the groups manually or automatically,[9] announcing one's presence and intention to the participants, and extracting the WhatsApp messages from the groups after some

[9] This can be done using the WhatsApp Web API and the Selenium package for R or python.

time. The approach has been improved by Bursztyn and Birnbaum (2019) with a script that automatically adds invite links that are shared in joined groups to the total list of groups to be joined. Other researchers asked friends and acquaintances to let them join their family groups to gain access to private conversations (Garcıa-Gómez 2018) or created their own group for role-play experiments (Sprugnoli et al. 2018).

Data donation. Another approach to collect WhatsApp chat log data is to ask participants of the respective chats to export and donate their chat logs to the researchers. Most studies using this approach rely on opt-in participation with some sort of public advertising to promote the study and/or some sort of compensation for participation. For example, Verheijen and Stoop (2016) created a website, promoted the study on campuses and national radio and TV shows, and organized a raffle to motivate participants to take part in the study. Despite these efforts, only 34 participants donated their WhatsApp chat logs. However, using a similar approach, the "Whats up, Switzerland" project (Ueberwasser and Stark 2017) created a website that was advertised on several Swiss news outlets and managed to collect 967 donated chat logs. In contrast, Seufert et al. (2015) approached 250 participants in Germany and asked for their participation in a study about WhatsApp. Participants had to fill in a questionnaire, look up and indicate their own WhatsApp usage statistics, and were also asked to donate a WhatsApp group chat log. Using this approach, over 274 group chats were donated, with some participants donating even more than one chat. In a related study, Schwind and Seufert (2018) described how they built an automated system, that allows participants to send their chat logs to an email address to be automatically processed, anonymized, and stored in a database. In exchange for participation, participants receive a code that allows them to access visualizations and statistics about their sent-in chats.

11.3.2 Incentivizing Participants

Due to the often very private content of WhatsApp chat logs and some effort on the side of participants, one major challenge is to incentivize people to donate their chat logs for research purposes or to let researchers join their public group to extract data. One form of motivation is to rely on private connections with friends and acquaintances to support the researcher (Garcıa-Gómez 2018). This approach has the advantage of low effort on the side of the researcher but is otherwise severely methodologically limited. First of all, the potential sample that can be acquired with this method is rather small and extremely selective, not allowing for any kind of population inference. Secondly, members of the group chat are aware that the researcher is joining the group, likely influencing their subsequent behavior. This is especially limiting because when joining a chat, one can only extract messages from the point of joining but none of the messages that were sent before. Another form of incentivization is self-benefit (cf. Skatova and Goulding 2019), for example through monetary compensation or the opportunity to win a prize. This approach is frequently used for survey studies and experiments. However, in the context of WhatsApp data donation, it has not seemed to be effective so far (cf. Verheijen and Stoop 2016). Another approach to motivate research participants to donate data is to **provide insight** about their own behavior through tailored feedback. It is sometimes used in survey or experimental studies (Singer and Ye 2013), for example in studies about personality (Montag et al. 2019) or smartphone usage (Montag et al. 2015). Despite requiring the setup of additional technical infrastructure, it has several advantages. First of all, it is cost-efficient because it does not require additional funding for raffle prizes or monetary compensation. Second, it allows researchers to sample from a larger population than their immediate friends and family. Third, by having the data donated instead of joining the group, the data are not biased by the presence of the researchers. Most importantly however, the approach seems to be quite effective in motivating participants to share their data (Seufert et al. 2015; Schwind and Seufert 2018). If and how people who are convinced to share their data by feedback differ from those who do not has not been investigated to the best of our knowledge so far. Researchers employing this approach should thus devote special attention to participants who drop out of the study and the resulting consequences for population inference.

11.3.3 Data Processing

Once WhatsApp chat log data are collected from participants, they must be processed to extract variables of interest and parsed into a suitable format for subsequent quantitative analysis. Chat logs extracted from WhatsApp come as a plain, unencrypted, utf8 encoded txt file. In general, every line of the text file corresponds to one message beginning with a timestamp, followed by the name of the sender (as it appears on the phone from which the message was extracted), and then the body of the message. Messages only expand to several lines in the exported chat log if users manually inserted line breaks into their messages. Importantly however, the structure of the chat log file differs depending on multiple factors such as the operating system of the phone with which the data were extracted, time settings of the phone, language settings, and whether the data were extracted with or without media files. For example, a general difference between Android and iOS phones is that the timestamp includes seconds in iOS but not on Android. Chat logs extracted from iOS devices thus have higher temporal resolution than those from Android phones. With respect to structure, the timestamp is encased in brackets in iOS logs but not in Android logs, and timestamp and name of sender are separated through a dash on Android but not on iOS (see Codeblock 11.1).

Another general difference between WhatsApp chat logs exported from Android and iOS phones is the way in which attached media files are represented in the chat log. In general, when the option to export no media files is selected, messages that contain media files are replaced with < Media omitted > . However, when media files are exported, the chat log will also list their names and file types, depending

```
1/29/18, 23:45 – Bob:  This is an example for Android phones.

[1/29/18, 23:45:03] Bob: This is an example for iOS phones.
```

Codeblock 11.1 Example messages from chat logs extracted from Android and iOS phones

on the operating system of the exporting device. While Android lists the file name and extension first, followed by the text "(file attached)", iOS encases the message text in angle brackets and preludes file name and type with the text "attached:" (see Codeblock 11.2). The file names contain the timestamp when the message was sent, and an enumeration indicating the number of total files of this type sent in this conversation.

In addition to these overarching structural differences, exported chat logs also differ with respect to the time and language settings of the phone from which the chat log is extracted. For example, the format of the timestamp at the beginning of the message depends on time settings set on the phone and can either be in 24 h format or 12 h format (see Codeblock 11.3).

Yet another important feature of exported WhatsApp chat logs are **system messages**. These are messages that are not created by participants of the chat but are inserted into the chat by WhatsApp. For example, each chat log starts with the message that the conversation is end-to-end encrypted and has additional messages for certain events, for example when participants change their phone number, the group is renamed, new members are added, members leave the group, or the group icon is changed. These messages will have a timestamp and indicate the person who performed the action but not separate their name from the rest of the message with a ":". Importantly, the messages are inserted in the language corresponding to the exporting phone's language setting, which is not necessarily the same as the language of the chat. To automatically detect system messages, it is thus important to know the language setting of the exporting phone. Importantly, different language settings

```
1/29/18, 23:46 – Alice:  PTT–20180129–WA0025.opus (file attached)

[1/29/18, 23:46:03] Alice:  <attached: PTT–20180129 –WA0025.opus>
```

Codeblock 11.2 Example messages from chat logs extracted from Android and iOS phones containing sent media files. The file extension .opus stands for recorded WhatsApp voice messages

```
1/29/18, 23:45 – Bob: Yes it is!

1/29/18, 11:45 PM – Bob: Yes it is!
```

Codeblock 11.3 Example messages from chat logs extracted from two Android phones with different time settings

```
1/29/18, 12:24 – Messages to this group are now secured with end-to-end
                 encryption. Tap for more info.
1/29/18, 12:24 – You created group „GROUPNAME1“
1/29/18, 12:24 – You added Mallory
1/29/18, 12:24 – Mallory: Hey, what’s up? :)
1/29/18, 12:24 – You removed Mallory
1/29/18, 12:25 – You added Alice
1/29/18, 12:26 – You changed the subject from „GROUPNAME1“ to
                 „GROUPNAME2“
1/29/18, 12:26 – You changed this groups icon
1/29/18, 23:46 – Alice: PTT-20180129-WA0025.opus (file attached)
```

```
29.01.18, 12:24 – Nachrichten an diese Gruppe sind jetzt mit Ende-zu-ende
                  Verschlüsselung geschützt. Tippe für mehr Infos.
29.01.18, 12:24 – Du hast die Gruppe „GROUPNAME1“ erstellt
29.01.18, 12:24 – Du hast Mallory hinzugefügt
29.01.18, 12:24 – Mallory: Hey, what’s up? :)
29.01.18, 12:24 – Du hast Mallory entfernt.
29.01.18, 12:25 – Du hast Alice hinzugefügt.
29.01.18, 12:26 – Du hast den Betreff von „GROUPNAME1“ zu
                  „GROUPNAME2“ geändert.
29.01.18, 12:26 – Du hast das Gruppenbild geändert.
29.01.18, 23:46 – Alice: PTT-20180129-WA0025.opus (Datei angehängt)
```

Codeblock 11.4 Example messages from chat logs extracted from two Android phones with the same time settings but different language settings. The changed language setting also changes the formatting of the date in the timestamp. The system messages inserted by WhatsApp into the chat do not specify a sender name but can contain chat participant names

can also influence the date format in the timestamp of the messages (see Codeblock 11.4).

A further issue with respect to the preprocessing of exported WhatsApp chat logs is the encoding. Because the chats are encoded as a utf8 text file, researchers need to make sure to open the files using the same encoding standard. If the wrong encoding is used, special characters (e.g. $, €, ä,ü,á) and emoji[10] will be formatted incorrectly. From our experience, this is especially problematic when using the Windows operating system because, as opposed to MacOS or Linux, the standard encoding on Windows is CP-1252.[11] Last but not least, WhatsApp offers the opportunity to either automatically delete messages after seven days or to manually delete one’s own messages for up to one hour after they were sent. For deleted messages, the message body is replaced

[10] https://cran.r-project.org/web/packages/utf8/vignettes/utf8.html.

[11] https://en.wikipedia.org/wiki/Windows-1252.

with "You deleted this message" in the chat log file. In addition, there is the opportunity to manually delete messages sent by other people any time. However, these messages are only deleted from the log file of the respective person but will be contained in the chat logs of all other chat participants. Images or videos that are sent with the auto-deletion feature show up as empty messages in the chat log files.

Overall, exported WhatsApp chat logs allow researchers to extract timestamps, names of senders, system messages, message text, as well as sent file names and types with automated methods by leveraging the structure of files. Importantly, researchers need to devote special attention to the time settings, language settings, and operating system of the phone from which the chat was extracted to ensure correct parsing of the chat logs. In addition, researchers need to ensure that the chat logs are opened with the correct encoding, that chat messages and system messages can be distinguished, and determine if data were deleted from the chats by participants. With respect to the message bodies themselves, it is possible to extract further information (e.g. used emoticons and emoji, sent locations, sent links or domains, mentioned users in group chats) using text mining mining tools like RegEx.[12] For practical examples see Sect. 5.

11.4 Research Ethics and Data Protection

As WhatsApp chat logs are extremely private and often contain highly personal information, ethical collection, processing, and storage of the data are of utmost importance. Despite several studies working with this kind of data, there seems to be no gold standard method yet, with different strategies having been put forward to ensure ethical handling in different studies. Most of these studies have reflected on the ethical implications of working with WhatsApp chat logs, but little to no work has been devoted to explicitly establishing general guidelines for working with exported chat logs (see Barbosa and Milan 2019 for an exception). In the following section, we will discuss and comment on the ethical implications of working with WhatsApp chat logs and how they have been addressed in several previous studies. Most issues can be summarized in the domains of informed consent, using raw data versus using metadata, protection of personal data, and on reproducibility versus privacy.

11.4.1 Informed Consent

Informed consent refers to the practice of researchers informing study participants about the nature and any risks associated with their participation in a study and the opportunity for participants to drop out at any point without negative consequences. Importantly, for consent to be considered "informed", research participants

[12] https://en.wikipedia.org/wiki/Regular_expression.

must have an understanding of the procedures they are subjected to, and the data that they provide (cf. Nunan and Yenicioglu 2013). Informed consent is a debated topic in social media research (e.g. Williams et al. 2017; Salmons 2017), because a great deal of information (e.g. Facebook posts or Tweets) is shared by people with full awareness of the data being publicly available for anyone. As such, some argue that obtaining explicit informed consent might not always be necessary when conducting research with publicly available data (see Townsend and Wallace 2016 for a discussion). WhatsApp is fundamentally different, because the data on peoples' profiles or statuses are only available to others who have their telephone number in their contact list, and chat logs are only accessible to participants of the respective chats. Consequently, obtaining people's informed consent is essential for conducting ethical research with WhatsApp data. This issue has been approached differently in multiple studies using WhatsApp chat logs. For example, studies using the method of Garimella and Tyson (2018), typically use an opt-out procedure with the researchers joining public WhatsApp groups and announcing their presence and the nature of their study. If they are not removed from the group or people explicitly announce their non-consent, consent is assumed for all members of the chat. We argue that this approach is inherently problematic due to at least two reasons. First, there is no way to ensure that participants actually read the message posted by the researchers in the group chat. Not revoking consent might thus be a consequence of not having read the message instead of consenting to contributing data to the research project. Second, new members who join the group after researchers posted their announcement cannot see it and are unaware of their data being used for research purposes. While some studies acknowledge this shortcoming (e.g. Narayanan et al. 2019), the approach is still frequently used (Resende et al. 2019; Machado et al. 2019; Tausczik and Pennebaker 2010; Resende et al. 2019; Melo et al. 2019; Bursztyn and Birnbaum 2019; De Freitas Melo et al. 2019).

Other studies rely on explicit opt-in procedures to guarantee informed consent, often by combining survey studies with voluntary data donation (Seufert et al. 2015; 2016; Verheijen and Stoop 2016; Ueberwasser and Stark 2017; Schwind and Seufert 2018). Typically, participants in these studies are asked to export the chat logs on their own phones and send them to the researchers via email. This procedure ensures that data donors are aware of their data being used for research purposes and gives them the opportunity to actively look into the file they are donating. However, some issues remain controversial. First, some studies collect informed consent from all participants of the chat (Sampietro 2019; Flores-Salgado and Castineira-Benitez 2018; Sprugnoli et al. 2018; Raiman et al. 2017; Smit 2015; Garcıa-Gómez 2018; Ueberwasser and Stark 2017; Montag et al. 2015), but others only collect consent from donors of the chat (Seufert et al. 2015, 2016; Verheijen and Stoop 2016; König 2019). Of these studies, some simply delete the messages of chat partners (Verheijen and Stoop 2016) or reduce them (or all messages) to basic metadata (Seufert et al. 2015, 2016), while others ask donors to ensure that all participants have consented to donation (König 2019).[13] Other studies do not explicitly mention how consent of chat donors (De Vel et al. 2001; Bursztyn and Birnbaum 2019) or other chat participants (Rosenfeld et al. 2018; Schwind and Seufert 2018; Petitjean and Morel 2017) was managed.

The multitude of used approaches highlights that obtaining consent is a difficult issue for this kind of data. Incentivizing research participants to donate WhatsApp chat logs is already a difficult task, and many researchers seek to design the donation procedure as convenient as possible. Obtaining explicit opt-in consent from all chat participants is certainly the most rigorous way to approach consent, but often greatly increases the time and effort required for data donors and could thus drastically reduce study sample sizes. Many studies circumvent this issue by not asking all chat participants for consent and simply discarding their messages afterwards or anonymizing their names and telephone numbers while reducing the message bodies to metadata. Whether this approach is justifiable is not an easy question to answer as it needs to balance ethical concerns with practical affordances of conducting innovative studies. However, we argue that informed opt-in consent from all participants of the chats should be the gold standard for ethical research, even if direct identifiers are deleted or chats are reduced to metadata.

Consequently, we provide a process by which informed opt-in consent could be implemented for all chat participants in a semi-automated way: Researchers could ask data donors to paste a statement of consent drafted by the researchers into the chat, informing all participants and asking them to answer with a predefined message if they consent to their data being used. After data donation, an algorithm could then automatically remove messages from all participants that did not answer the statement with the consent message. This approach would ensure that active consent can be obtained from all chat participants and content provided by non-consenting chat participants can be automatically deleted before the researchers have access to the data. However, the increased effort on the side of participants might reduce willingness to donate data in the first place.

11.4.2 Raw Data versus Metadata

Besides the way in which informed consent is obtained in studies using exported WhatsApp chat logs, one important ethical decision is whether to use raw chat logs or only use metadata extracted from the chats. By raw data, we refer to the unencrypted, plain-text content of sent messages in this case, while metadata refer to any characteristics of messages (e.g. number of characters, timestamp, whether a link is contained), that do not give away the content of the message. In general, this is a trade-off between being as parsimonious as possible with collecting highly sensitive data and obtaining the most detailed dataset possible. This is not only an

[13] The following corpora were used in the study: https://db.mocoda2.de/c/home, https://smsdbms.sprache-interaktion.de/.

ethical question but also a methodological one. For some research questions like the spread of visual misinformation through WhatsApp (Narayanan et al. 2019), the network traffic caused by WhatsApp (Seufert et al. 2015), or response patterns in group chats (Seufert et al. 2016), extracted metadata might be sufficient. However, other research questions regarding argumentative strategies (Garcıa-Gómez 2018) or emotional expression (Sampietro 2019) can require the raw data to be preserved for qualitative analysis. Even if researchers should restrict themselves as much as possible regarding collecting sensitive raw data, the kind of research question they are interested in might sometimes still justify working with raw chat logs. Another approach is to explicitly ask participants whether they are comfortable with sharing their chats in raw format, or if they prefer that only metadata are used (Seufert et al. 2015). Importantly however, WhatsApp chat logs can only be extracted as raw data, meaning that if researchers decide to restrict themselves to metadata, there needs to be an automated system for parsing the chat logs and extracting the metadata from them. Because this system works with raw data as input, special attention should be given to testing and securing it, so that no unencrypted raw data are exposed. For examples on how such systems could be set up, see Schwind and Seufert (2018); Narayanan et al. (2019); Resende et al. (2019a); Rosenberg and Asterhan (2018).

11.4.3 Protection of Personal Data

Raw exported WhatsApp chat logs contain personal data (PD) in multiple forms that need to be protected by researchers. In the General Data Protection Regulation, PD is defined as “any information relating to an identified or identifiable natural person (‘data subject’); an identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person” (Council of European Union 2016). Exported WhatsApp chat logs contain both, direct and indirect information that might result in the recognition of a data subject. First of all, exported WhatsApp chat logs contain names of the senders as they are saved in the contact list of the exporting person or their telephone number if they are not saved in the exporter’s contact list. This direct information is not only contained in parts of the chatlog indicating who sent a message but can also be contained in the system messages. For example, when the name of the group is changed by Person A, the chatlog will contain a system message in the style of: “Person A changed the subject from GROUPNAME1 to GROUPNAME2″. The same issue occurs for people changing their phone numbers, changing group icons, adding or removing people from groups, or leaving the group (see Codeblock 11.4). Secondly, the content of the messages might contain indirect information, such as people mentioning the name of the street they live on, names of partners or family members, links to their online accounts, their place of work, or any other information that could help to identify them.

This issue can be approached by researchers with anonymization or pseudonymization. Anonymous data is defined as "information which does not relate to an identified or identifiable natural person or to personal data rendered anonymous in such a manner that the data subject is not or no longer identifiable" (Council of European Union 2016). In contrast, pseudonymization constitutes "the processing of personal data in such a manner that the personal data can no longer be attributed to a specific data subject without the use of additional information, provided that such additional information is kept separately and is subject to technical and organisational measures to ensure that the personal data are not attributed to an identified or identifiable natural person" (Council of European Union 2016). In essence, anonymization means that all information that could lead to identification is removed from the data while pseudonymization means that a link between data and participants can still be established in principle, but only when using additional information (e.g. replacing real names with pseudonyms and keeping a list matching pseudonyms and real names in a separate file).

In the context of WhatsApp chat logs, different studies have employed various methods for protecting participants' privacy. For larger, quantitative studies, typically with donated data, removal of usernames and telephone numbers is the standard. The most frequently used methods are to replace the names and telephone numbers of all senders with placeholders, ensuring that senders stay distinguishable from each other in the corpus (or at least within the same chat log) without compromising their privacy. This method is relatively straightforward to implement as the parts in the messages or system messages where names or telephone numbers are inserted are structured and can be automatically detected and replaced using RegEx[5]. If this information is completely removed without keeping a separate file matching the original information to the placeholders, the procedure constitutes an effort to anonymize the data.

However, not only the names of participants or their telephone numbers constitute PD. The content of the messages can also contain information that could be used to reidentify a participant. For this reason, some studies only collect metadata in the first place (Rosenberg and Asterhan 2018), while others collect raw data but aim to anonymize the message bodies afterwards. Approaches include manual anonymization through replacing names, numbers, and other PD with placeholders (Ueberwasser and Stark 2017), self-anonymization by data donators (König 2019) or automatic reduction of raw chats to necessary metadata (Narayanan et al. 2019; Machado et al. 2019; Resende et al. 2019; Schwind and Seufert 2018; Bursztyn and Birnbaum 2019; De Freitas Melo et al. 2019; Sprugnoli et al. 2018). Some studies did not use any of these approaches or provide no information about their anonymization procedures (Raiman et al. 2017; Smit 2015; Garcıa-Gómez 2018).

Over and above, we want to highlight that raw chat messages are inherently difficult to anonymize. First of all, WhatsApp chats are fundamentally unstructured as people can input any information in any form they like, making it essentially impossible to anticipate which kinds of privacy-relevant information might be contained. This is problematic for automated methods and manual methods alike, as both rely on an underlying system to code the messages as privacy-relevant or not. Second, while manual methods might work better for detecting subtle, uncommon instances of PD in chat logs (e.g. somebody spelling out the digits of their phone number in words), they do not scale well to larger data collections. Third, automated methods for inferring demographic attributes like age (Tam and Martell 2009), gender (Cheng et al. 2011), ethnicity (Rao et al. 2011; Levitan et al. 2016), sexual orientation (Lynch et al. 2019), or nationality (Massung et al. 2013) from text data are constantly evolving and could facilitate reidentification of participants in the future. In fact, Rosenberg and Asterhan (2018) already demonstrated that gender and age group can be inferred from metadata of WhatsApp chat logs without access to message content. Fourth, the way people interact through instant messaging is highly personalized. As such, people could potentially be identified by their **idiolect**, defined as an "individual's unique way of writing with respect to vocabulary, grammar, punctuation, or other lexical features".[14] For example, Pappert (2017) describes the case of a couple that ritualized using a specific pattern of emoji in their communication (💍 💍 ⚓). Likewise, the author describes two friends who routinely use a sequence of emoji with the last emoji being context dependent (🐢💨💩+ context emoji). These features are extremely difficult to detect and replace and could theoretically help identify participants, for example by searching for these patterns in publicly accessible social media. Even for chats reduced to metadata, machine learning and data mining techniques might help to predict attributes of the participants that could help to reidentify them assuming malice, advanced know-how, and sufficient motivation. For a general overview of automatic authorship attribution, see Madigan et al. (2005) and Zheng et al. (2006); for practical examples see De Vel et al. (2001); Argamon et al. (2009); Orebaugh and Allnutt (2009); Narayanan et al. (2012); Coulthard (2004).

Due to the issues outlined above, some security researchers argue that for text data, there can never be a guarantee that anonymization procedures will make a reidentification impossible on principle and that there will always remain a risk of reidentification given enough time, effort, know-how, and/or technological progress (Finck and Pallas 2020; Mozes and Kleinberg 2021; Moretón and Jaramillo 2021). Even though other regulations partly use stricter criteria for data to be considered anonymous, a remaining risk for reidentification is also acknowledged in the GDPR for anonymous data (cfg. Finck and Pallas 2020). Following this argument, whether a data set containing text can be considered anonymous or not is not a simple yes or no question but should be based on an individual risk assessment and testing for the respective dataset at hand. The question that researchers should seek to answer is hence not whether reidentification is (and will always be) impossible, but whether it is sufficiently difficult, unlikely and inconsequential for study participants to consider the data anonymous (cfg. Finck and Pallas 2020; Mozes and Kleinberg 2021; Moretón and Jaramillo 2021). For example, one method to test the effectiveness of an anonymization procedure is to use a motivated intruder test, where testers with no special know-how but access to the internet and public records are asked to reidentify people from a dataset. The number of correctly deanonymized participants and the kind of information that the testers can extract from the dataset can serve as

[14] https://en.wikipedia.org/wiki/Idiolect.

a benchmark for evaluating the effectiveness of an anonymization procedure. For a detailed discussion of strategies to assess anonymization procedures for unstructured data see Mozes and Kleinberg (2021) and Moretón and Jaramillo (2021). For practical advice on testing the effectiveness of anonymization strategies with motivated intruder testing, see for example guidelines of the UK Information Commissioner's Office (2012).

In sum, exported WhatsApp chat logs contain personal data in multiple formats and must be treated with extreme caution. The names and telephone numbers of senders need to be replaced with placeholders or removed in front of the message body and in WhatsApp system messages to prevent direct identification of study participants. Message bodies can either be processed manually or automatically in an effort to remove personal data, which we argue is inherently problematic due to the unstructured nature of text data. Notably, even reducing the message bodies to metadata is not an uncontestable guarantee that further information cannot be inferred by sophisticated machine learning models. Researchers thus should not simply apply standardized anonymization procedures and assume their data is unproblematic afterwards but rather reflect on the likelihood, difficulty, and consequences of deanonymization for their specific data set. After contemplating these issues, they could employ a motivated intruder test to evaluate the effectiveness of their anonymization procedure for the data that they intend to share.

11.4.4 Reproducibility versus Privacy

For transparent and reproducible research, scientific data should be findable, accessible, interoperable, and reproducible.[15] Naturally, this is especially challenging for highly sensitive data that contains PD, such as WhatsApp chat logs. The question regarding if and how to make collected WhatsApp chat log data accessible to other researchers is thus a difficult trade-off between transparency and reproducibility on the one hand, and the privacy of research participants on the other hand. The simplest solution to this issue is, of course, to err on the side of caution and not share the collected data at all (e.g. Garcıa-Gómez 2018; Pappert 2017; Seufert et al. 2015, 2016; Sánchez-Moya and Cruz-Moya 2015; Maız-Arévalo 2018; Sampietro 2019; Petitjean and Morel 2017). Other studies do make data available (on request), either as metadata with anonymized author names (Montag et al. 2015; Garimella and Tyson 2018), or manually anonymized raw messages with anonymized author names (Sprugnoli et al. 2018; Ueberwasser and Stark 2017; König 2019).

Which of these approaches is an ethically sound choice depends on all previously outlined factors: If and how informed consent was obtained, if raw or metadata are included in the dataset, and if and how senders and message bodies were anonymized. Because all of these factors also depend on the kind of research question one seeks to answer with the data, there is no "one size fits all" approach to ethical sharing

[15] https://www.go-fair.org/fair-principles/.

of data from WhatsApp. We would thus agree with the suggestion of Barbosa and Milan (2019), to not reduce ethics in this domain to a simple checklist that can be implemented without further consideration. Rather, researchers should critically reflect on the potential harm they might cause participants and if their autonomy over their data might be violated (Barbosa and Milan 2019). Nevertheless, we provide some guidance about the issues that researchers should contemplate when working with data from WhatsApp in Sect. 6 of this chapter.

11.5 WhatsR—an R-Package for Parsing and Visualizing WhatsApp Chat Logs

In this section, we focus on applied methods for processing and analyzing WhatsApp chat logs and present an R-package built for scientists who want to work with WhatsApp data. The package is still in development and thus not yet available on CRAN but can already be downloaded from GitHub.[16] It is a useful tool for WhatsApp chat log preprocessing and analysis but does not liberate researchers from critically reflecting on the design of their studies, informed consent, protecting personal information, or secure IT architecture. The most important feature of the package is the parse_chat() function (see Codeblock 11.5), which takes raw exported WhatsApp text files as input and returns a parsed version of the chat log as an R dataframe. The function has parameters for parsing chats from Android and iOS phones and automatically detects and converts the time format. The package uses a list of regular expressions to differentiate chat messages from system messages and to detect sent files indicators (if included in the export). It currently supports English and German chats but can easily be expanded to other languages by manually including the respective regular expressions. The parser extracts the following information from the chats and saves them as columns in a dataframe with one message per row:

Datetime The date and time for each WhatsApp message is detected and converted into a datetime object. For chats exported with Android phones, the timestamp is exact to the minute while for chats exported from iOS devices, the timestamp is exact to the second. The common format of the datetime object is yyyy-mm-dd HH:mm:ss, for example 2018–01-29 12:24:00.

Sender The sender column contains the name of the sender of the message as it is saved in the contact list of the phone from which the WhatsApp chat is exported. If the sender is not saved in the contact list of the exporting phone, their phone number is indicated instead. For WhatsApp System messages, the parser inserts “WhatsApp System Message” into the sender column. Importantly, the sender column can be anonymized automatically by setting the anon parameter in the parse_chat() function to TRUE. By doing so, all names and telephone numbers in the sender column will

[16] https://github.com/gesiscss/WhatsR.

```
Dataframe <- parse_chat(PathToYourTxTFile,
                        EmojiDic = “internal”,
                        smilies = 2,
                        anon = TRUE,
                        media = TRUE,
                        web = “domain”,
                        order = “both”,
                        language = ”english”,
                        os = “android”)
```

Codeblock 11.5 Example for the parse_chat() function

be replaced, ensuring that privacy is preserved but participants are still recognizable as the same person within the same chat (e.g. “Person_1”).

Message The message column contains the raw message body text containing all emoji, emoticons, links, numbers, and special characters. However, emoji are detected and converted into a human-readable form. Specifically, they are replaced by their official name[17] in snake case, prefixed by “Emoji”, and encased in “|”. For example, 😄 will be replaced with “|Emoji_Grinning_face_with_smiling_eyes|”. Through the *EmojiDic* parameter in parse_chat(), users can decide whether to use an included dictionary of emoji or supplement a custom dictionary.[18]

Flat This column contains a reduced version of the raw message body. In this version, emoji, emoticons, numbers, and special characters have been removed. This version is more convenient to use for additional natural language processing.

TokVec This column further reduces the flat message body to a list of tokens that were separated by a space or by punctuation. It is more convenient for word level analysis and counting the number of words per message. Every element in this column is not a single string but a list of strings and needs to be treated as such in R.

URL The URL column contains a list of all links that are contained in the raw message body. By setting the *domain* parameter to TRUE in the parse_chat() function, the links will be shortened to domain names. For example, “https://github.com/gesiscss/WhatsR“ would be shortened to ”https://github.com”. Every element in this column is not a single string but a list of strings and needs to be treated as such in R.

Media The media column contains a list of the names of sent files, including their respective file endings. As such, the column will be empty for chats that were exported with the “without media files” option. Every element in this column is not a single string but a list of strings and needs to be treated as such in R.

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[17] https://emojipedia.org/

[18] See also the download_emoji() function in the same package.

Location This column contains a list of Google Maps links as representations of shared locations within messages. The links contain the longitude and latitude of the shared location in high resolution. Shared live locations are indicated by the text string “live location shared”, but no actual location data are stored in exported chat logs for live locations. Every element in this column is not a single string but a list of strings and needs to be treated as such in R.

Emoji Contains a list of all emoji contained in the raw message body in human-readable format. For example, 😁 will be replaced with “Emoji_Grinning_face_with_smiling_eyes”. Trough the *EmojiDic* parameter in parse_chat(), users can decide whether to use an included dictionary of emoji or supplement a custom dictionary[11]. Every element in this column is not a single string but a list of strings and needs to be treated as such in R.

Smilies Contains a list of all emoticons (e.g. “;-)”) contained in the raw message body. Through the smilies parameter in parse_chat(), users can decide whether to use an included dictionary of emoticons or supplement a custom dictionary.[19] Every element in this column is not a single string but a list of strings and needs to be treated as such in R.

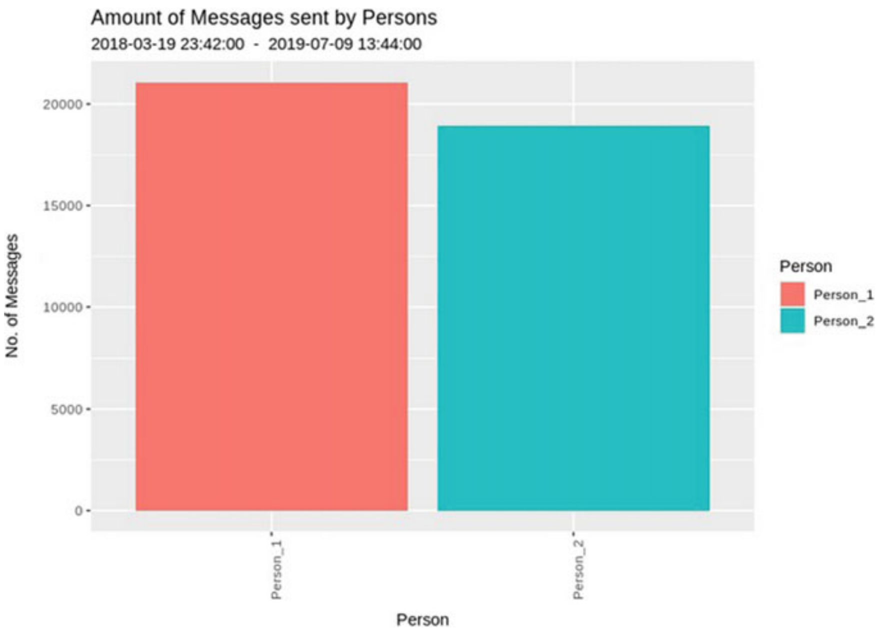
TokCount The token count is a single value representing the number of tokens per message, based on the TokVec column.

System Messages Includes the raw message body of all WhatsApp system messages that are automatically inserted into the chat by WhatsApp. By setting the anon parameter in the parse_chat() function to TRUE, all names and phone numbers included in the sender column are replaced in the System Message column as well. However, names or numbers of chat participants who are members of the chat but do not appear in the sender column (i.e. those who never sent a message in the chat), cannot be detected this way. For the final version of the package, an improved method to anonymize system messages based on RegEx patterns will be implemented.

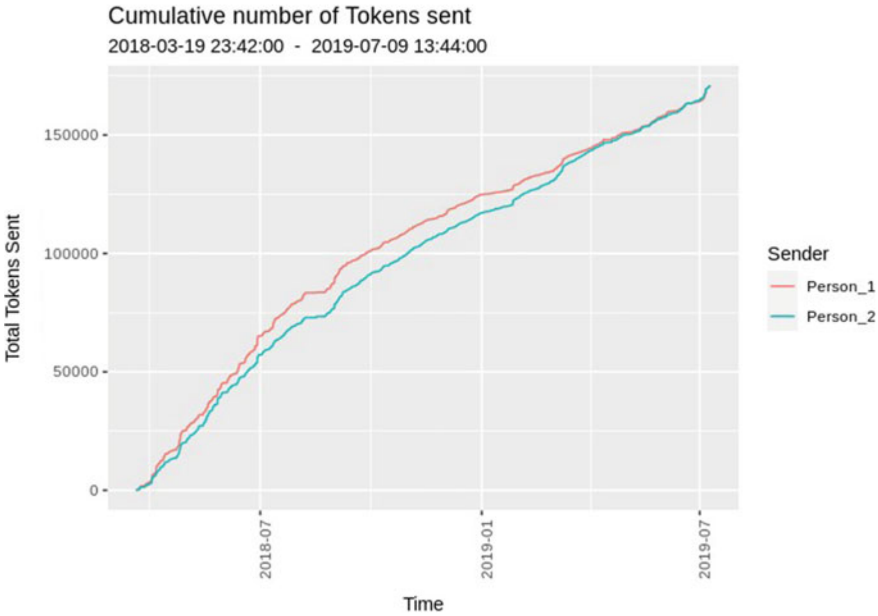
Using the parse_chat() function in our package results in an R dataframe object that is easy to work with for text mining, natural language processing, or other quantitative statistical analyses. It also offers researchers some convenience functions to anonymize sender names, shorten links to domains, translate emoji into human-readable format, and extract interesting features such as emoji, links, locations, sent files, or emoticons from the text. Moreover, the package contains several functions to visualize variables of interest. Some examples are showcased in Figs. 11.3 and 11.4; for a more complete list, see our GitHub repository.

With this package, we hope to support scientists with extracting variables of interest, anonymization, and visual exploration of donated WhatsApp chat logs. The package might be used as a basis for a data collection pipeline, where chat logs can be donated online and are automatically parsed, anonymized, and reduced to the necessary metadata. Nevertheless, the package should be used responsibly and is by no means a replacement for methodological and ethical contemplation and a secure

[19] See also https://en.wikipedia.org/wiki/List_of_emoticons

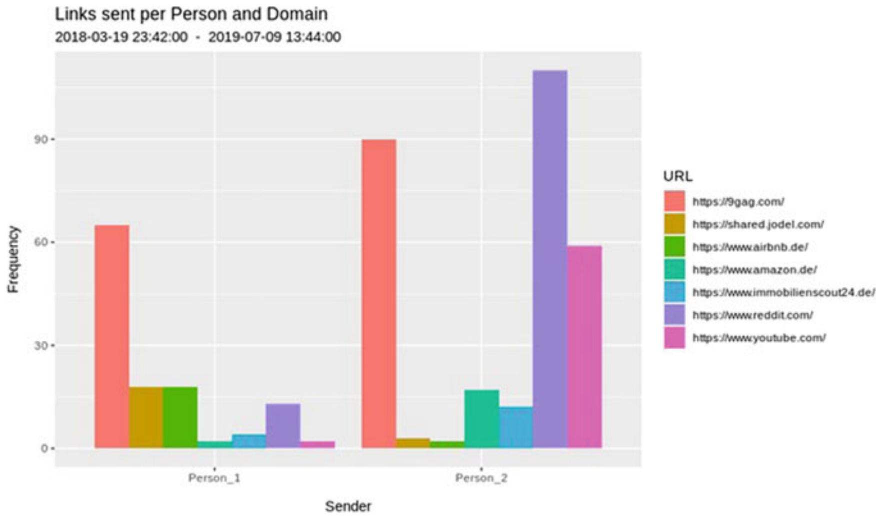


(a) Amount of total messages

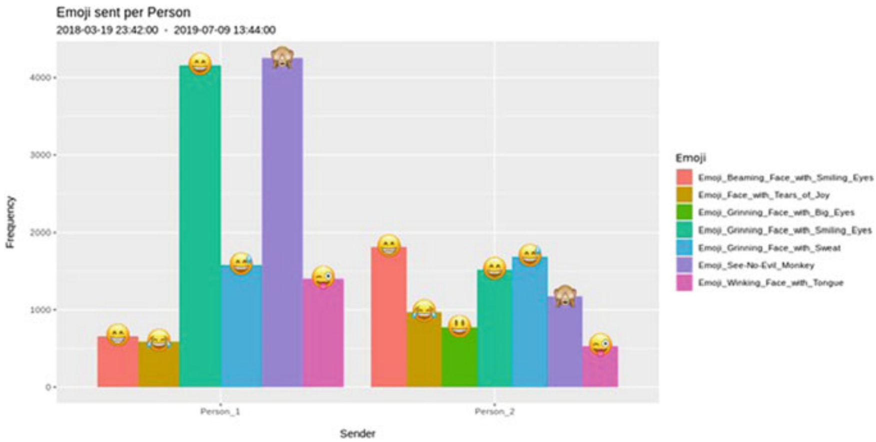


(b) Number of cumulative tokens sent over time

Fig. 11.3 Example plots of visualizations from the WhatsR package. Chat logs were provided by one of the authors with explicit consent of chat partners for anonymous data use



(a) Domains of sent links



(b) Most frequently used Emoji

Fig. 11.4 Example plots of visualizations from the WhatsR package. Chat logs were provided by one of the authors with explicit consent of chat partners for anonymous data use. For links, only domains which occurred more than 20 times in the chat were plotted. For emoji, only those that appeared more than 100 times in the chat were plotted

research design and technical infrastructure. It should not be used without rigorous testing for the use case at hand and setup of additional measures for encryption or participant feedback and consent.

11.6 A Practical Guide for WhatsApp Data

Even though every research project is different and there are usually no general solutions to issues regarding methodology, ethics and data protection for unstructured data such as text (Mozes and Kleinberg 2021; Barbosa and Milan 2019), we would like to provide some structure and advice for contemplating these important questions. This is not meant as a checklist but as food for thought when conducting research with chat log data from WhatsApp or similar data. We hope that this might help researchers to reflect more thoroughly on these issues while designing studies and hence contribute to exploit the potentials of this intriguing kind of data even better.

Data Collection One of the most fundamental questions for research with data from WhatsApp is how to collect the desired data. Researchers can either join a public or private WhatsApp conversation themselves or ask participants of a conversation to export and donate their data. The crucial difference between these two approaches is that in the former, participants are aware of the presence of the researchers while the data is generated, while in the latter data can be collected retrospectively. For research questions where the awareness of a researcher's presence is likely to influence the outcome to be measured, we thus recommend using retrospective data donation to avoid potential biases in the collected data.

Incentivization To incentivize potential participants to donate their data and consent to subsequent analysis, a combination of media advertisements for the study and providing feedback about participants' chat behavior has worked best in previous studies. In contrast, providing financial incentives has not shown much success for motivating potential participants to donate data. Another aspect that might play a role but has not been investigated in this context so far is being transparent about which data is processed, how it is secured, and what the goals of the study are. Devoting special attention to reassure participants that researchers respect and ensure their privacy might enhance their willingness to participate (see below).

Informed Consent Participants should be fully aware of their data being collected, what the collected data looks like, what their data will be used for, how it will be processed, and if it will be publicly available. Special contemplation should be given to consent from participants of chats who are not actively donating their own data. Those participants should provide opt-in consent as well, especially when raw data are collected instead of metadata and researchers are planning to share the data later. One way of ensuring informed consent is to ask the data donor to inform all other participants in the chat of their intention to donate the data and ask them to copy and paste a consent statement drafted by the researcher into the chat. Data from senders of messages who did not post the exact consent statement into the chat could subsequently be identified and removed with automated methods.

Raw Data versus Metadata While some research questions necessitate the analysis of raw message bodies, we argue for processing the collected data as parsimoniously as possible. Researchers should reduce the chat logs to metadata that are sufficient to answer their own research questions but not contain any additional information that is not strictly necessary. While this reduces the reusability of collected data, it also reduces the danger of potential reidentification of study participants and the potential consequences should reidentification occur. In addition, data processing should be automatized whenever feasible so that exposure of raw data to humans is reduced as much as possible.

Anonimization The absolute minimum requirement for anonymization of WhatsApp chat logs is the removal of direct identifiers such as sender names and telephone numbers from the start of messages and message bodies. However, message bodies can contain any number of indirect information that might help to reidentify study participants. As we have outlined above, no manual or automatic anonymization procedure is provably infallible for removing such information from texts. This is why we recommend reducing the chat logs to metadata whenever possible (see above). Metadata is more difficult to deanonymize and the potential consequences for deanonymized metadata are less severe than for altered message bodies. For research questions that require working with messages instead of metadata, researchers should not assume that their anonymization procedures make their data completely anonymous by design. Rather, they should critically reflect on the likelihood, difficulty, and consequences of deanonymization for their specific data set. A motivated intruder test could be a way to assess the quality of anonymization and point out potential flaws before data is shared or made public.

Data Sharing Researchers are responsible for who is able to access the collected data after the study is finished. While public availability is the gold standard for reproducible research, protecting the privacy of participants should always have higher priority. For data to be shared, all participants of the chat logs in question should have provided their informed consent for data collection and subsequent sharing. Furthermore, the data should be reduced to metadata as much as possible. If the content of messages is necessary to reproduce the findings, messages need to be stripped of direct identifiers such as names and telephone numbers and indirect identifiers such as street names, names of relatives, or workplaces. Because no anonymization procedure is guaranteed to remove all identifiers, researchers should test their anonymization procedure before sharing the data, for example using a motivated intruder test. Even if data seems unproblematic to share at the time, availability on request seems to be a sensible compromise for most chat log data.

Data Processing and Analysis WhatsApp chat logs can only be exported as unencrypted utf8 text files and thus require special measures to ensure secure and ethical processing. Infrastructure used to transfer chat log files from study participants to researchers should encrypt the files, and researchers should use automated procedures for preprocessing the data in such a way so that human contact to raw chat logs is minimized. At a minimum, direct identifiers such as sender names and telephone numbers should be deleted from the chat. Depending on the research question at hand, message bodies should be reduced to metadata as much as possible or anonymized with tested procedures (see above). Because the structure of exported WhatsApp chat log files depends on the language and time settings on the exporting phone, its operating system, and whether media files were included in the export, researchers need to test their automated processing systems for all possible constellations of these factors and assess them rigorously.

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Part III
Applications in Health Sciences

Chapter 12
Latest Advances in Computational Speech Analysis for Mobile Sensing

Nicholas Cummins and Björn W. Schuller

Abstract The human vocal anatomy is an intricate anatomical structure which affords us the ability to vocalise a large variety of acoustically rich sounds. As a result, any given speech signal contains an abundant array of information about the speaker in terms of both the intended message, i.e., the linguistic content, and insights into particular states and traits relating to the speaker, i.e., the paralinguistic content. In the field of computational speech analysis, there are substantial and ongoing research efforts to disengage these different facets with the aim of robust and accurate recognition. Speaker states and traits of interest in such analysis include affect, depressive and mood disorders and autism spectrum conditions to name but a few. Within this chapter, a selection of state-of-the-art speech analysis toolkits, which enable this research, are introduced. Further, their advantages and limitations concerning mobile sensing are also discussed. Ongoing challenges and possible future research directions in relation to the identified limitations are also highlighted.

12.1 Introduction

Human speech is produced by an exceptionally complex and intricate interaction between our cognitive and neuromuscular systems (Fitch 2000; Levelt et al. 1999). As a result, speech is a highly sensitive output system; physiological, pathological and biochemical changes easily affect our speech production in ways that are audible and thus objectively measurable using intelligent signal analysis and machine

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_12

learning methodologies. Indeed, there are a plethora of papers in the relevant literature highlighting the benefits of using speech as an objective marker for a wide range of emotional, pathological and mental health conditions, e.g., (Bone et al. 2017; Cummins et al. 2015; Schuller et al. 2018a, b; Schuller 2017). This work is centred in a field of research known as *computational paralinguistics* (Schuller and Batliner 2013), which is the extraction and analysis of the phenomena embedded into a speech signal. This information includes short-term speaker states such as one's current instantaneous level of arousal or valence, or longer-term speaker traits such as if a speaker is currently suffering a mood disorder or similar condition. Within computational paralinguistics, frequently studied pathological and mental health conditions include unipolar and bipolar depression (Cummins et al. 2015; Ringeval et al. 2018), autism spectrum conditions (Ringeval et al. 2016; Schuller et al. 2013), and Parkinson's disease (Orozco-Arroyave et al. 2016; Schuller et al. 2015).

The richness of information available in a speech signal is further complemented by the ease at which it can be collected remotely and unobtrusively. With the ongoing growth of the *Internet-of-Things* (IoT), microphone embedded smart devices and wearable technologies are at the point of ubiquity in modern society (Jankowski et al. 2014). This growth has enhanced researchers and clinicians, ability to collect data relating to, not only speech (Cunningham et al. 2017; Hagerer et al. 2017; Marchi et al. 2016; Tsiartas et al. 2017), but a wide array of bio- and behavioural markers. Such data can, in turn, be used to aid (early) detection and remotely monitor a wide range of conditions (Istepanian and Al-Anzi 2018).

The aim of this chapter is two-fold. The first aim is to introduce the reader to a range of intelligent audio signal processing toolkits. These toolkits, the OPENSMILE feature extraction tool (Sect. 12.2), the OPENXBOW crossmodal Bag-of-Words toolkit (Sect. 12.3), the DEEPSPECTRUM (Sect. 12.4) and AUDEEP (Sect. 12.5) Python-based toolkits for feature representation learning, as well as the END2YOU toolkit for multimodal end-to-end profiling (Sect. 12.6), allow users to easily and quickly extract rich and relevant information from speech and audio signals. Where relevant, the use of this toolkits in analysing other behavioural- and bio-signals is also highlighted. These toolkits are introduced as they are all open source and are widely prevalent in the relevant literature. Further, they have all been used as baseline systems within the popular *Computational Paralinguistics Challenge* (COMPARE) and *Audio/Visual Emotion Challenge* (AVEC) workshops, see (Ringeval et al. 2018; Schuller et al. 2018a, b) for the 2018 challenge papers, among other challenges, and can, therefore, be regarded as standards in the field of audio signal processing.[1] The second aim is to discuss current challenges associated with speech-based mobile sensing and, to this end, highlight possible future research direction (Sect. 12.7). The chapter finishes with a brief concluding statement (Sect. 12.8).

[1] Nicholas Cummins is a co-developer of the DEEPSPECTRUM and AUDEEP toolkits. Björn W. Schuller is a co-developer of all five toolkits.

12.2 OPENSMILE

OPENSMILE[2] is a well-established research tool in speech, music and audio processing (Eyben et al. 2010, 2013). OPENSMILE enables users to, in real-time, extract large—knowledge driven—audio feature spaces. Feature extraction, in terms of intelligent signal processing, is the extraction of information relevant to the task at hand. For speech analysis, the extracted information is generally prosodic-acoustic in nature. A wide set of speech features can be extracted using openSMILE including *prosodic* features, such as loudness and pitch; *voice quality* features, such as jitter and shimmer; and *spectral* features, such as Mel-/Bark-/Octave-spectra, mel-frequency cepstral coefficients and spectral shape descriptors. All speech-related features extractable through OPENSMILE are grounded in highly researched and well-documented theories which, due to room limitations will not be discussed herein. For further information relating to speech and audio feature extraction, the interested reader is referred to (O'Shaughnessy 1999; Quatieri 2002).

OPENSMILE itself, is a cross-platform toolkit capable of operating in *Windows*, *Linux*, *Mac* and *Android* environments. It can receive a wide set of inputs including *audio* (.wav), or previously extracted features in *comma separated value* (.csv) or text (.txt) formats. The toolkit, as well as extracting a wide set of audio and speech *low-level-descriptors* (LLDs)—features—from a given input, also provides support for the post-processing of these LLDs such as through smoothing filters and standardisation and normalisation. The extraction of most speech and audio LLDs is conducted in very short analysis windows (typically 25–40 ms in length), paralinguistic effects on the other hand, are often more evident in the evolution of these features over time (Schuller and Batliner 2013). In this regard, OPENSMILE also supports feature summarisation (over a chunk of time or the course of an utterance) using statistical functionals. Finally, OPENSMILE has a range of output options including playback (.wav), .csv, and .txt files. Support is also provided (both an input and output) for common machine learning platforms such as the *.arff* format for the WEKA platform (Hall et al. 2009); LIBSVM (Chang and Lin 2011); and HTK (Young et al. 2002).

As well as enabling the extraction of numerous audio features, a core strength of openSMILE is its ability to extract this information in real-time; as enabled by the platform's unique modular architecture. Data flow is handled by a central memory component which essentially manages a combination of data processing components each configured to perform a particular task. Each component has permission to write to one memory location but has permission to read from other component's memory locations. This permission set-up enables a highly efficient incremental computation procedure in which a specific task, needed in multiple steps in a feature extraction pipeline, is only performed once (Fig. 12.1).

As already mentioned, the OPENSMILE toolkit has been used for baselines within the COMPARE and AVEC workshops. Within these challenges, participants are supplied with a common dataset and have to perform a specific classification or

[2] https://www.audeering.com/technology/opensmile/.

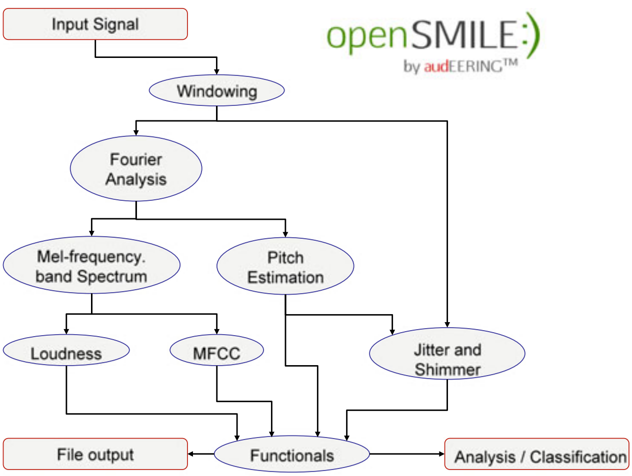

Fig. 12.1 An example of an incremental computation procedure enabled by OPENSMILE's unique modular architecture. In this example shows the information flow between different processing components needed to extract supra-segmental representation of loudness and pitch, both prosodic features; Mel Frequency Cepstral Coefficients (MFCC), a spectral feature representation; and both the Jitter and Shimmer voice quality features. Note, figure adapted from processing (Eyben et al. 2013)

regression task on this data; OPENSMILE is used to provide participants with a baseline feature set. The exact make-up of this feature set has evolved over the course of the challenges, and has now settled into two commonly used representations; the 6,373 dimensional 'paralinguistic omnibus' feature set known as the *Interspeech Computational Paralinguistics Challenge features set* (COMPARE) (Eyben et al. 2013), and the 88 dimensional 'tailor-made' for emotion recognition feature set known as the *extended Geneva Minimalistic Acoustic Parameter Set* (EGEMAPS) (Eyben et al. 2016). The scripts needed to implement the extraction of both the COMPARE and EGEMAPS, as well as scripts for a variety of other standard speech and audio features is provided with the OPENSMILE software.

12.3 OPENXBOW

OPENXBOW is a Java-based program for generating *bag-of-words* representations from either acoustic LLDs, transcriptions of natural speech, or visual features such as facial action units (Schmitt and Schuller 2017), physiological features or any other kind of time series feature data. The bag-of-words approach originated from natural language processing, where documents are classified based on a histogram representation of linguistic features such as the actual words present in the document. A *Bag-of-Audio-Words* (BoAW) on the other hand, involves quantisation of acoustic

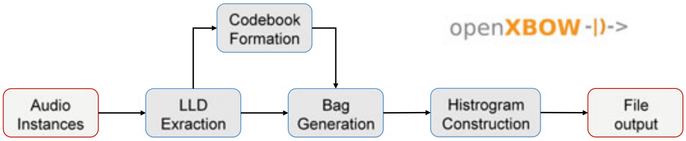

Fig. 12.2 A generalised overview of the key step involved when extracting a bag-of-audio-words feature representation using OPENXBOW. Note, figure adapted from (Schmitt and Schuller 2017)

LLDs with respect to an audio word from a previously learnt codebook. BoAW representations have been shown to produce state-of-the-art results in a variety of audio classification tasks, in particular, continuous speech-based emotion prediction (Schmitt et al. 2016) and depression detection (Joshi et al. 2013). Visual features can be treated in a manner to form *Bag-of-Video-Words* (BoVW) representations, which have also been shown to be well suited to tasks such as emotion prediction (Ringeval et al. 2017) and sentiment analysis (Cummins et al. 2018a).

As already mentioned, a bagged feature representation is a sparse multi-dimensional feature space formed by the quantisation (bagging) of LLDs. This bagging procedure follows four keys steps (Fig. 12.2). First, is the extraction of the LLD features, using the openSMILE toolkit for instance. Second, a codebook is learnt from designated training data. In OPENXBOW the codebook can be performed by one of two methods, either by k-means clustering, or by a 'random' sampling of all LLDs in the training set. The default random sampling implemented in OPENXBOW is the initialisation step of the k-means clustering; the codebook entries are selected subsequently by a methodology which favours vectors which are farther away—as determined via Euclidean distance—from those already selected. The third step is the assignment of each frame-level LLD vector to words in the formed codebook. This assignment is achieved by identifying the vector in the codebook which returns the minimum Euclidean distance with the input vector. OPENXBOW also allows assignments to multiple codebook vectors; i.e., the quantisation is performed with respect to a predefined number of 'close' codebook entries again, as determined using the Euclidean distance. Finally, by counting the number of assignments for each word, a fixed length histogram (bag) representation of an audio clip is generated. This histogram represents the frequency of each identified word in a given input instance (Schmitt and Schuller 2017).

OPENXBOW supports two input and three output format types: *.csv* and *.arff* inputs and outputs are supported, while the LIBSVM file format is also supported but as an output only. OPENXBOW also offers a range of pre-processing options including normalisation and standardisation of the LLD's and post-processing options for normalising and reweighting the extracted histogram. The interested reader is referred to the OPENXBOW software repository for full details.[3]

In terms of mobile sensing, bagged feature representations offer several key advantages. Bagged representations are sparse by nature, with this property essentially

[3] https://github.com/openXBOW/openXBOW.

controlled by two parameters: the *codebook size* (Cs) which determines the dimensionality of the final feature vectors, and the *number of assignments* (Na) which determines the number of words assigned to an audio instance. Sparsity offers the advantages of being more computationally efficient, it costs less memory, and it is quicker to perform multiplication operation on sparse representations. Bagged feature spaces are also time-invariant; a single fixed length vector is generated regardless of the length of the input utterance; in its post-processing options, OPENXBOW allows users to normalise the extracted histogram with respect to the length of the input file. Further, recent research has shown that BoAW representations are more robust to noise in the LLD feature space (Cummins et al. 2017a); it is speculated that this is due to the quantisation step which allows this technique to have a degree of tolerance to small perturbations in the input data.

Finally, increasing consumer ethical awareness and legal frameworks, such the recently introduced *General Data Protection Regulation* (GDPR) in the European Union, has pushed issues relating to privacy to the forefront of current challenges in mobile and IoT based health applications (Kargl et al. 2019). In this regard, the OPENXBOW reduces the risks associated with recording, transmitting and analysing data. Primarily, the quantisation step undertaken when bagging features can be considered privacy conserving as the resulting time-invariant histogram of occurrences cannot be used to reconstruct the input space. Moreover, no critical information seems to be lost in this transformation, in general through tuning Cs and Na a BoAW representation can be found which outperforms more conventional speech and audio representations, e.g., Cummins et al. (2017b); Schuller et al. (2018a, b); Schuller et al. (2017).

12.4 DEEPSPECTRUM

Fuelled by high profile examples in popular media, interest in artificial intelligence applications, in particular, deep learning, has never been stronger. Deep learning itself is a particular subset of machine learning algorithms containing a vast set of interconnected nodes whose structure is inspired by the structure and function of neurons in the human brain. A deep learning model can be considered a multi-layered pipeline of non-linear transformations, capable of representing highly complex decision functions while maintaining a high degree of generalisability. Advances in deep learning have undoubtedly been responsible for dramatic increases in system robustness and accuracy in a number of audio and speech applications. However, due in part to securing adequate amounts of reliable training data, deep learning has not had the same dominating effect in speech-based health detection systems commonly associated with mobile sensing applications (Cummins et al. 2018b).

Deep learning can, however, be leveraged in these applications through techniques such as transfer learning and unsupervised feature extraction. The use of neural networks, or other machine learning paradigms, as a feature extractor is commonly known as *representation learning*. Handcrafted features, such as those extracted using

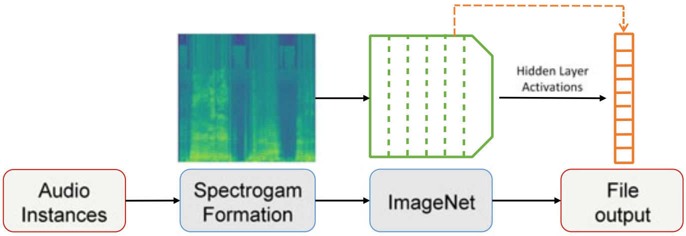

Fig. 12.3 An overview of extracting DEEPSPECTRUM features. Audio samples are converted to spectrogram images and then feed into a pre-train image classification Convolutional Neural Networks (CNNs); the activations of fully connected layers are then used as a feature representation for subsequent classification

OPENSMILE, have come about through engineers, or scientist somewhat subjectively select the relevant prosodic or acoustic property to extract; the extraction process is typically based on well-established theorems which can take decades to refine. Representation learning, on the other hand, is the development of techniques which enable machines to learn the discriminative characteristics of raw data or LLDs automatically. Learnt representations have many desirable properties, in particular, they can be easily adapted to suit a change in system requirements, such as different input data or classification targets (Bengio et al. 2013).

Convolutional Neural Networks (CNNs) have been continually proven adept at representation learning tasks. CNNs usually contain a combination of convolutional (filtering), pooling layers and non-linear activations which can learn a hierarchy of different feature representations, from broad in the initial layers to more task-specific in the later layers (LeCun et al. 2015). Indeed, it is standard practice in image processing to use the activations of different layers of so-called *imageNets* CNNs, trained on over a million images (Krizhevsky et al. 2012; Simonyan and Zisserman 2014), to perform feature extraction in other visual classification tasks. A somewhat recent fascinating result from computational speech analysis shows that imageNets can also produce meaningful speech, and audio feature representations for tasks such as emotion recognition and bipolar mood state, for example, (Cummins et al. 2017a; Ringeval et al. 2018) and audio features for tasks such as irregular heart sound detection (Ren et al. 2018). This approach, utilising pre-trained for image nets to extract audio feature representation from spectrogram images, is known as DEEPSPECTRUM feature extraction (Amiriparian et al. 2017a, b).

The DEEPSPECTRUM toolkit[4] is a python-based repository, for this extraction procedure. The core steps involved in DEEPSPECTRUM feature extraction are essentially choosing a suitable image representation of a speech segment and choosing which pre-trained image net to use as the feature extractor (Fig. 12.3). Currently, in terms of image formation, the DEEPSPECTRUM repository supports spectrogram,

[4] https://github.com/DeepSpectrum/DeepSpectrum.

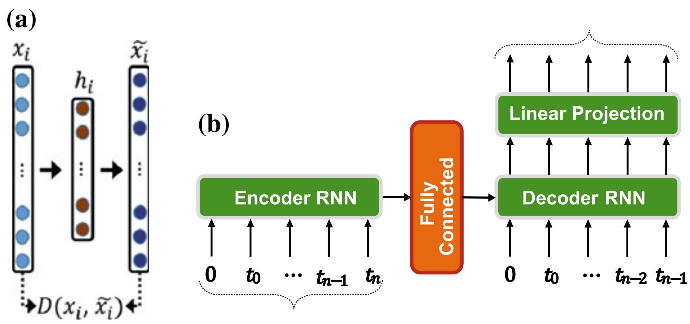

Fig. 12.4 AUDEEP's strengths lie in the recurrent sequence to sequence autoencoder technology implemented in the toolkit. The goal of autoencoders **a** is to create a robust representation of a data instance by passing it in through a neural network which attempts to recreate its input at its output. The inclusion of recurrent layers in the encoder and decoder parts if the network **b** enables the network to learn a fixed length representation of a variable length signal. Note, figure adapted from (Amiriparian et al. 2017a, b; Freitag et al. 2018)

chromagram and mel-spectrum representations, while any image net in the Caffe-TensorFlow toolkit,[5] including ResNet 50, VGG 16, GoogLeNet, or AlexNet, are supported. Deep spectrum features are given as the system output in either *.csv* or *.arff* formats. Fine-grained control and support, especially in relation to spectrogram formation, is available within the toolkit; the interested reader is referred to the repository for full details.

12.5 AUDEEP

The AUDEEP toolkit is a Python/tensorflow based repository for deep unsupervised representation learning from acoustic data.[6] One limitation of the CNN feature learning approach is difficulty in handling variable length data, as commonly found when working with audio data. The most common method for dealing with this is to divide audio files into overlapping chunks resulting in a lack of temporal continuity between the chunks. AUDEEP negates this limitation by implementing a recurrent sequence to sequence autoencoder for deep unsupervised representation learning (Amiriparian et al. 2017a, b; Freitag et al. 2018). Autoencoders are a specific type of neural networks which are designed to reconstruct its input data at its output while attempting to learn a robust 'compressed' representation of the data in its hidden layers (Fig. 12.4a). When implemented with recurrent neural networks, which can encode temporal data, it is possible to learn a fixed length representation of a variable length signal. Within AUDEEP, the sequence to sequence autoencoder is augmented with a fully connected layer between a multilayered *encoder* RNN, and another

[5] https://github.com/ethereon/caffe-tensorflow.

[6] https://github.com/auDeep/auDeep.

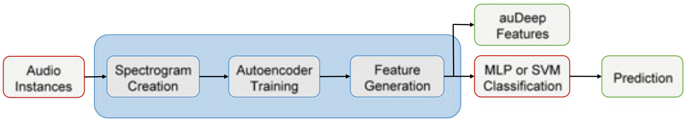

Fig. 12.5 To create AUDEEP feature representations, spectrograms are first extracted from raw audio files. Then, a recurrent sequence to sequence autoencoder is trained on the extracted spectrograms and the learnt representation of each instance is extracted as a feature vector. If the user has supplied instance labels, a classifier can then be trained and evaluated on the extracted features. Note, figure adapted from (Amiriparian et al. 2017a, b; Freitag et al. 2018)

multilayered *decoder* RNN (Fig. 12.4b). Once trained, the activations of this fully connected layer are used as a feature representation. AUDEEP representations have been used in tasks such as acoustic scene classification (Amiriparian et al. 2017a, b), irregular heart sound detection (Amiriparian et al. 2018), atypical and self-assessed affect detection as well as infant cry recognition (Schuller et al. 2018a, b).

Taking a high-level overview of the feature extraction processes, the AUDEEP toolkit has four key steps (Fig. 12.5). First, the input data is converted into spectrogram or mel-spectrum based representations. Subsequently, the deep recurrent sequence to sequence autoencoder is trained on these spectra. Features can then be generated by passing the spectra back through the network and extracting the activations of the fully connected layer. Finally, AUDEEP utilises the Scikit-Learn toolkit (Pedregosa et al. 2011), to implement a *Multilayer Perceptron* (MLP) or *Support Vector Machine* (SVM). Alternatively, the user can choose to output the learnt representations as either a *.csv* or a *.arff* file. AUDEEP's command line interface offers a fine level of control over each step, with a large selection of related hyperparameters to tune.

The large amounts of hyperparameters, and the need to train deep neural networks themselves with numbers of parameters up into the millions, is a current limitation of applying AUDEEP in mobile sensing applications. However, the same can currently be stated of practically any deep learning system; put simply, the potential of DNNs has yet to be fully exploited in embedded systems as many state-of-the-art neural networks paradigms require too much memory to fit in on-chip storage (Han et al. 2015b; Zhu and Gupta 2017). Further, they have high computation demands to run efficiently in embedded devices (Chen et al. 2017; Han et al. 2016; Lane et al. 2016). This is discussed further in Sect. 12.7.

12.6 END2YOU

A recent exciting development in deep neural network technologies is the advancement of *end-to-end learning*. End-to-end learning takes the feature representation paradigm a step further by learning the entire classification pipeline directly from *raw* data instances (Trigeorgis et al. 2016). In doing so, hand-engineered features

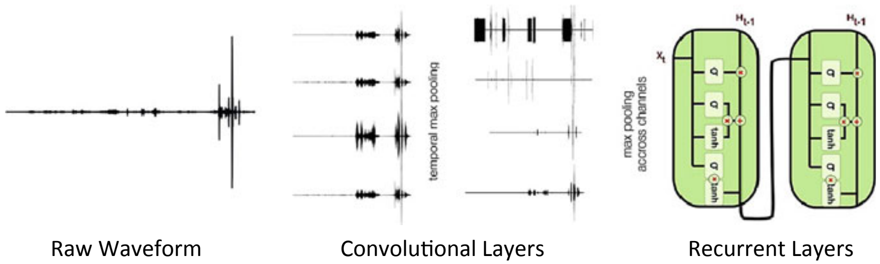

Fig. 12.6 An example of an end-to-end deep learning system pipeline. First, the raw data is divided into blocks of 40 ms, the raw instances are then fed into convolutional layers which learn a suitable feature representation, and recurrent layers are used to capture relevant temporal dynamics from the learnt features. Note, figure adapted from (Trigeorgis et al. 2016)

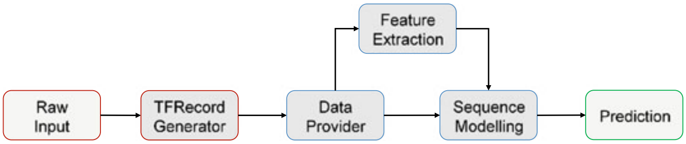

Fig. 12.7 The END2YOU pipeline consists of the *.tfrecord* generator, the data provider that feeds either the data through a feature extraction model (Convolutional Neural Network) into a sequencing model (Recurrent Neural Network) or, if desired, directly into the sequencing model, and finally the prediction model to generate the final output. Note, figure adapted from (Tzirakis et al. 2018)

are removed entirely from an analysis pipeline; instead, the network learns its own robust feature representation specific for the task it is being trained on. End-to-end systems typically consist of *convolutional* layers to learn robust feature representations followed by *recurrent* layers to leverage the temporal dynamics inherent in time-series data such as speech (Fig. 12.6). A fully connected layer can then be used to map between the output of the recurrent layers to the output score space. In terms of mobile sensing, notwithstanding current issues relating to deploying deep neural nets on embedded devices, is they offer a potential solution to alleviate privacy concerns by deploying an entire classification tool on a smart device.

The END2YOU toolkit,[7] implemented in python and based on Tensorflow, provides users with the capability of performing end-to-end learning on audio and visual systems (Tzirakis et al. 2018). Taking a generalised overview of the system, the workflow consists of two phases (Fig. 12.7). First, the raw signals are converted into Tensorflow's *.tfrecord* format; after that, it is possible to train and evaluate a model. During this second phase, a data provider unit reads the *.tfrecords* files, and feeds this information into the convolutional layers for feature extraction; this extracted information is then passed on to the recurrent layers for sequence modelling with the final step being the mapping to the prediction space using a fully connected network. Note that, it is also possible to pass the raw *.tfrecords* directly into a recurrent network.

[7] https://github.com/end2you/end2you.

The default audio system provided in End2You is composed of a 2-block of convolution max-pooling layers; the first layer has 40 filters of size 20 with a pooling of size 2; the second layer has 40 filters of size 40 with a pooling layer of size 10. The default visual feature extractor is the ResNet-50 network (He et al. 2016). For both modalities, the default recurrent system is a 2-layer *Gated Recurrent Unit* network with 64 units. For further details on the toolkit, the interested reader is referred to (Tzirakis et al. 2018).

End-to-end learning has been used in a diverse array of tasks such as emotion detection (Trigeorgis et al. 2016), snore sound recognition, cold, and flu detection (Schuller et al. 2017), as well as irregular heart sound, or typical and self-assessed affect and crying detection (Schuller et al. 2018a, b). It has also been used to profile physiological signals, such as electrocardiogram and electrodermal activity for emotion detection (Keren et al. 2017). On large emotion detection databases, end-to-end learning has achieved state-of-the-art performances (Trigeorgis et al. 2016). However, the advantages of end-to-end learning are not as clear when tested on smaller datasets, and often unbalanced in terms of class distributions, typically found in health sensing applications. It has been speculated this effect is related to the training of an end-to-end model essentially on the statistics available in raw data representations. In this regard, smaller and unbalanced datasets may contain insufficient variation, especially concerning the underrepresented class, for robust end-to-end modelling (Schuller et al. 2017).

12.7 Challenges and Future Work Directions

Due to the richness of health information embedded into speech signals, paralinguistic analysis should be considered a core information stream in any health-based mobile sensing platform. However, to herald in the next generation of speech-enabled smart devices, future work directions need to focus around enabling deep learning approaches in smart and embedded devices. This challenge is highly non-trivial as current state-of-the-art deep learning solutions are large and computationally demanding models. Furthermore, for many somatic/physical and mental health conditions that may be of interest in a mobile sensing platform, there are challenges related to collecting and labelling sufficient amounts of data to adequately train deep learning solutions.

Low Resource Neural Networks: The contemporary speech processing approaches discussed in the preceding sections, DeepSpectrum, auDeep and End2You, are based on neural networks. Such systems, which are capable of producing state-of-the-art results, have connection numbers measuring in the millions, potentially require hundreds of megabytes and create substantial data movement operation to support their computation. This makes them difficult to operate in the low resource and low power settings commonly associated with mobile sensing applications (Chen et al. 2017; Han et al. 2016; Lane et al. 2016). A growing research direction within neural networks is the development of approaches which can take

Table 12.1 A comparison of the advantages and disadvantage of different approaches to create a (computationally) low resource neural network

Approach	Advantages	Disadvantages
Network pruning	Applicable on pre-trained networks	Loss of precision
Mathematical optimisation	Applicable on pre-trained networks	Complexity of optimisation approaches
Knowledge distillation	A purpose built, smaller network is learnt	Increase in training time and effort
Spiking neural networks	Highly energy efficient	Require specialist hardware
Reconfigurable chips	Overcome memory bottlenecks	Require specialist hardware

in a large network and optimise it until it is executable on a low resource device (Table 12.1). Many of these approaches focus on reducing the *memory footprint*, how much memory is required to store and run a network, and the *computational complexity*, the number of required calculations and their precision, of a network while at the same time preserving its level of accuracy.

One such approach is *network pruning* which not only reduces the size of the model, but also as it reduced the number of free learning parameters can counteract overfitting (Cheng et al. 2017). The general assumption of this approach is that neural nets have a lot of redundant weights which do not considerably contribute to the performance of the network. Pruning removes such weights entirely; weight sharing between connections with similar weights can also be used to reduce the footprint of the network (Chen et al. 2015). The pruning of large dense models has even been shown to improve the performance while reducing the model size by up to 80% (Zhu and Gupta 2017). Another promising approach is *low precision* neural networks (Fig. 12.8); these are networks in which the associated parameter values are not stored in a high precision—float 32 for example—but rather in a simplified quantised representation (Gupta et al. 2015). For example, activations can be stored in either a binary, -1 or $+1$, or ternary -1, 0 or $+1$ format as an integer value. These approaches have been shown to considerably reduce memory and computation costs whilst maintaining reasonable accuracy (Alemdar et al. 2017; Han et al. 2015a).

A range of other approaches can be found in the relevant literature. *Mathematical optimisation* and *knowledge distillation* are two such approaches. Optimisation techniques such as low-rank approximations of weight vectors (Nakkiran et al. 2015) have been shown to decrease network size by 75%. Thereby, knowledge distillation approaches aim to train a smaller 'student' network which is able to perform the same task as a larger 'teacher' network (Cheng et al. 2017). Furthermore, a range of specialised hardware solutions are being explored such as neuromorphic computing running so-called *spiking neural networks* (Schuman et al. 2017) and reconfigurable chips such as *Field-Programmable Gate Arrays* (FPGA) which aim to overcome memory read/write bottlenecks common in conventional computing architecture

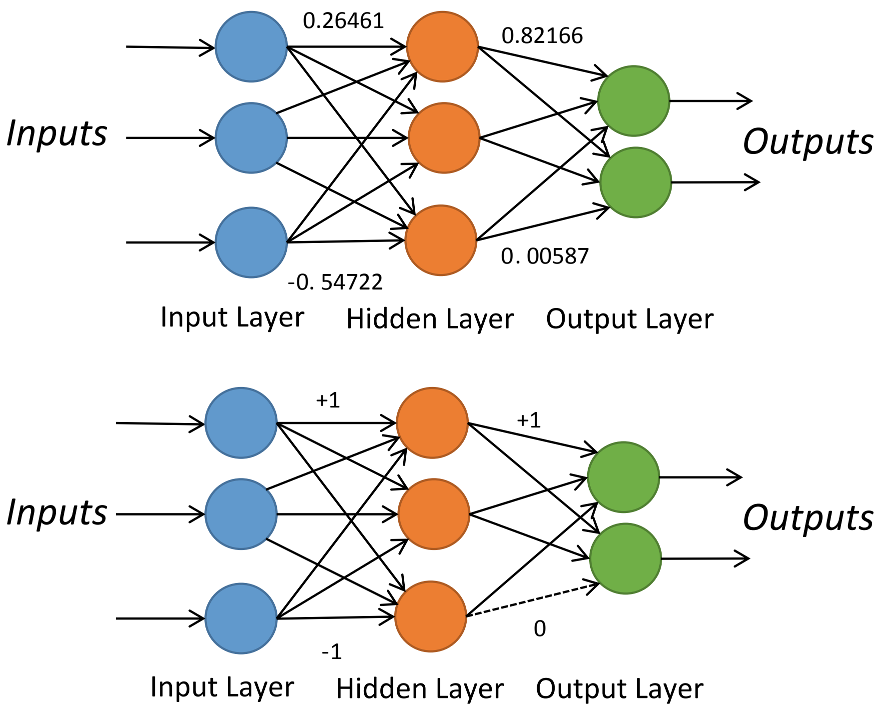

Fig. 12.8 An example of quantising weights in a neural network to form a low precision ternary neural network

(Ota et al. 2017). Google is also developing Tensor processing units specifically programmed for their TensorFlow framework (Jouppi et al. 2018), and are others developing *Neuro Processing Units* (NPUs).

As can be inferred from the above, low-resource network solutions are an active and growing area of research with many promising directions. Novel optimisation techniques and network topologies have shown promise in a range of learning tasks, but to date have yet to be fully explored for mobile sensing applications. In achieving such networks, researchers in mobile sensing applications cannot focus purely on system accuracy as their only evaluation metric—aspects such as runtime efficiency, noise robustness, generalisation, and energy consumption need to be considered as well during system design and development. Finally, developing networks increases the likelihood of systems being able to run offline, increasing user privacy and reducing energy consumption concerns associated with transmission bandwidth, both of which are core considerations for a robust mobile sensing unit.

Data Sparsity Challenges: A commonly occurring theme associated with speech databases for machine learning efforts into somatic/physical and mental health conditions is data sparsity. The corpora used to develop such systems are often small, both in terms of the total amount of speech data available and in the number of speakers present, and imbalance meaning they often contain more speech of individuals in a mild health state and noticeable less speech from individuals in a severe state. Such conditions make it difficult to train a model, especially deep learning models, which are well capable of generalising onto unseen data. However, ongoing research into *intelligent labelling* and *data augmentation* paradigms have the potential to alleviate these challenges.

Conventional data labelling paradigms require a large amount of time and resources to produce sufficiently reliable labels for machine learning. However, techniques such as semi-supervised learning, active learning, and cooperative learning have been shown to reduce these efforts (Zhang et al. 2017). These approaches leverage a smaller set of labelled data to annotate a larger dataset using machine learning techniques with minimal human involvement. Such methods have been shown to aid a wide range of speech-based classification techniques—in particular emotion and social signal recognition (Zhang et al. 2017). However, many of the advantages of many of these approaches have only been displayed in 'in laboratory' settings, and further experiments and advancements are needed to realise their suitability for mobile sensing platforms.

In this regard, future works should focus on integration, based around label confidence measures, in adaptive systems. Systems should be equipped with adequate confidence measures to perform co-operative adaptive learning; self-labelling data the system is highly confident about and interacting with the user to label data instances it has low confidence about but thinks are relevant to label and then utilising both sources of data to update its learning parameters to better match the user's need. Such systems should also focus on approaches, such as *few-shot networks*, that can efficiently solve new learning tasks requiring only a few instances of training data (Snell et al. 2017; Triantafillou et al. 2018).

Another potential method to address data sparsity concerns is data augmentation using techniques such as *Generative Adversarial Networks* (GANs) (Goodfellow et al. 2014; Han et al. 2018; Salimans et al. 2016) to generate new samples (Donahue et al. 2018; Saito et al. 2018). GANs consists of two neural networks: a *generative model* (generator) and a *discriminative model* (discriminator) which are set to compete against each other in a zero-sum game. During this game, the objective of the generator is to convert input noises from a simple distribution into realistic samples to fool the discriminator, while the objective of the discriminator is to distinguish between generated samples as being either '*real*' or '*fake*' (Fig. 12.9). The overall objective of the entire GAN network is to compel both models to continuously improve their methods until the generator is able to synthesise realistic data instances. Results published in (Deng et al. 2017), highlight the promise of GANs to mobile sensing applications. The authors demonstrated that GAN-based methods could be used to synthesise new training instances to aid a speech-based classification system to detect if a child was typically developing or had a developmental disorder such as an Autism spectrum condition.

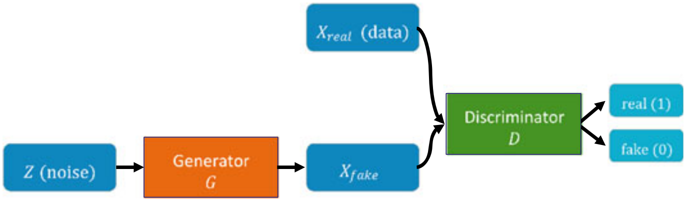

Fig. 12.9 The framework of *Generative Adversarial Network* (GAN); the objective of the generator is to fool the discriminator into misclassifying the generated samples while the discriminator is trained to accurately distinguish whether a given sample has been produced by the generator or drawn from a real data distribution. Training the networks concurrently in an adversarial setting allows the generator eventually produce realistic samples

12.8 Conclusion

As in most areas of intelligent signal analysis, deep learning has an unquestionable impact in computational speech analysis. While toolkits such as OPENSMILE and OPENXBOW are widely used due to their proven ability to generate robust audio and speech representations, there is a growing research interest in deep learning solutions, particularly for representation learning solutions that automatically and objectively learn meaningful feature representations. Results gained with the DEEPSPECTRUM, AUDEEP and END2YOU toolkits highlight the potential of representation learning across a range of computational paralinguistic tasks.

The toolkits discussed in this chapter, in combination with ubiquitous computing devices, place speech signals as a core modality for consideration in mobile health care solutions. However, to realise this, potential research efforts are needed to overcome challenges relating to the massive computational costs associated with current state-of-the-art neural networks and the data sparsity challenge associated in securing adequate data to train highly reliable and robust models. A combination of low resource deep learning paradigms, intelligent labelling solutions, and state-of-the-art data augmentation has the potential to foster in a new generation of mobile and intelligent patient-driven health care devices.

Acknowledgements This research has received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement No. 115902. This joint undertaking receives support from the European Union's Horizon 2020 research and innovation programme and EFPIA.

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Chapter 13
Passive Sensing of Affective and Cognitive Functioning in Mood Disorders by Analyzing Keystroke Kinematics and Speech Dynamics

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> Life is too sweet and too short to express our affection with just our thumbs. Touch is meant for more than a keyboard.
> — Kristin Armstrong, Olympic cyclist

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https://doi.org/10.1007/978-3-030-98546-2_13

Abstract Mood disorders can be difficult to diagnose, evaluate, and treat. They involve affective and cognitive components, both of which need to be closely monitored over the course of the illness. Current methods like interviews and rating scales can be cumbersome, sometimes ineffective, and oftentimes infrequently administered. Even ecological momentary assessments, when used alone, are susceptible to many of the same limitations and still require active participation from the subject. Passive, continuous, frictionless, and ubiquitous means of recording and analyzing mood and cognition obviate the need for more frequent and lengthier doctor's visits, can help identify misdiagnoses, and would potentially serve as an early warning system to better manage medication adherence and prevent hospitalizations. Activity trackers and smartwatches have long provided exactly such a tool for evaluating physical fitness. What if smartphones, voice assistants, and eventually Internet of Things devices and ambient computing systems could similarly serve as fitness trackers for the brain, without imposing any additional burden on the user? In this chapter, we explore two such early approaches—an in-depth analytical technique based on examining meta-features of virtual keyboard usage and corresponding typing kinematics, and another method which analyzes the acoustic features of recorded speech—to passively and unobtrusively understand mood and cognition in people with bipolar disorder. We review innovative studies that have used these methods to build mathematical models and machine learning frameworks that can provide deep insights into users' mood and cognitive states. We then outline future research considerations and conclude with discussing the opportunities and challenges afforded by these modes of researching mood disorders and passive sensing approaches in general.

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13.1 Introduction

Mood disorders take a sizable toll on the world's population, affecting more than 1 in 20 people annually and nearly 1 out of every 10 people over the course of their lifetime (Steel et al. 2014). Bipolar disorder, which alone accounts for at least 1% of years lived with disability globally (GBD 2017), is a mood disorder that causes patients to alternate between manic episodes of abnormally elevated mood and energy levels, and depressive episodes marked by diminished mood, interest, and energy (APA 2013). Compared to major depressive disorder (MDD), bipolar disorder can be harder to diagnose, and even when an accurate diagnosis is made, it is often delayed. The depressive episodes in both disorders share the same diagnostic criteria, and it is known that individuals suffering from bipolar disorder on average spend more time in the depressive phase than in mania. In particular, bipolar disorder type II, a subtype which is differentiated by attenuated levels of mania-like symptoms (termed hypomania) is difficult to diagnose by non-specialists as it can be challenging to distinguish from recurring unipolar depression. The presence of mood episodes with mixed features, i.e., those that exhibit characteristics of both mania and depression, can further complicate the process of diagnosis (Phillips and Kupfer 2013).

13.1.1 Current State of Diagnosis and Monitoring of Bipolar Disorder

Clinical approaches to diagnosing and monitoring bipolar disorder usually start with careful history-taking by the clinician (detailed interviews with patients and their family members as well as probing for a family history of the disorder), followed by the frequent use of self- and clinician-administered rating scales that assess for a history of possible mania or hypomania in patients with depression. Even with these tools at their disposal, it is often difficult for clinicians to ascertain whether any noted changes in mood, sleep, or energy are within normal ranges—or whether they are evidence of, say, a manic/hypomanic episode (Wolkenstein et al. 2011). Achieving inter-rater reliability between administered assessments and scales poses its own challenges.

After a correct diagnosis has been made, monitoring of symptoms commonly relies upon self-reports that may include mood charting and self-ratings or clinician-rated scales. These scales can only assess the severity of symptoms experienced by the patients and cannot actually screen for mania or hypomania; patients in manic states also may not be cognizant of their manic symptoms, casting doubt on the validity of some of these assessments (NCCMH 2018).

Ecological momentary assessments (EMA) have been used for supplementary monitoring in mood disorders with varying degrees of success (Ebner-Priemer and Trull 2009; Asselbergs et al. 2016; Kubiak and Smyth 2019). Asselbergs and colleagues reported that the clinical utility of self-report EMA is too often limited by the heavy response burden that is imposed upon respondents—which can result in large dropout rates after an initial period of activity—and furthermore, that the predictive models constructed using unobtrusive EMA data were inferior to existing benchmark models.

In recent years, other techniques including neuroimaging (Phillips et al. 2008; Leow et al. 2013; Ajilore et al. 2015; Andreassen et al. 2018) and genomics (Hou et al. 2016; Ikeda et al. 2017) have also been used in attempts to discover biomarkers for bipolar disorder. Although they may not currently be feasible either for diagnosis or for monitoring on an individual level, in the near future we may begin finding immense value in these and related methods beyond their immediate research applications.

In addition to its affective components, bipolar disorder also influences cognitive ability (APA 2013). Among the most severely impaired domains of cognition are attention, working memory, and response inhibition (Bourne et al. 2013). These provide another avenue to further aid in distinguishing a possible diagnosis of bipolar disorder from other mood disorders and assessing its course and treatment.

13.1.2 Passive Sensing in Physical Health

Smartwatches, fitness trackers, and associated physical health and fitness apps in general have to a large extent enabled and encouraged users to self-manage chronic medical conditions and attempt to take better care of their physical health (Anderson et al. 2016; Canhoto and Arp 2017; Messner et al. 2019). The Apple Watch, for instance—which uses photoplethysmography to passively sense atrial fibrillation—and the associated Apple Heart Study (Turakhia 2018) have already been credited with saving several lives by alerting enrolled users to the onset of life-threatening conditions and directing them to seek immediate medical attention (Feng 2018; Perlow 2018).

13.1.3 What About Passive Sensing for Mental Health?

Portable sensors to track the health of the rest of the body have so far proven easier to develop than those that can track brain health. As yet, there are no portable functional magnetic resonance imaging (fMRI) scanners or brain-computer interfaces (BCI) that can be used to unobtrusively analyze brain functioning—although science fiction has proposed examples of each in the form of, respectively, cowboy hats that conduct brain scans to map wearers' cognition in television shows such as Westworld (Avunjian 2018) and biomechanical computer implants called neural lace in author Iain M. Banks' series *The Culture* (Banks 2002, 2010)—which science may in fact someday deliver instead in the shape of the startup Openwater's fMRI-replacing ski hats that are purportedly being designed to use infrared holography to scan oxygen utilization by the wearer's brain (Jepsen 2017; Clifford 2017) and implantable electronic circuits capable of neural communication such as those being developed by Neuralink and others (Fu et al. 2016; Chung et al. 2018; Sanford 2018).

Until these nascent technologies reach maturity, there is a need for passive sensing tools that can bridge the divide and perhaps eliminate the need for more onerous means of sensing altogether. Smartphones are already ubiquitous enough and offer a wide array of sensors, which when used in concert with mHealth and digital phenotyping tools, offer a greater degree of precision medicine tools to users, researchers, and healthcare providers than ever before. Indeed, the very use of smartphones, and mobile social networking apps in particular, has been found to be associated with structural and functional changes in the brain (Montag et al. 2017); the corollary that smartphone usage patterns can be used to quantify the presence of established biomarkers has also been explored by Sariyska and colleagues (2018) in their preliminary study examining the feasibility of probing molecular genetic variables corresponding to individual differences in personality and linked social traits, in this case a variant of the promoter gene coding for the oxytocin receptor, and simultaneously surveying their real world behavior as reflected by the myriad different ways and purposes for which they used their phones over the course of the day.

The proliferation of touchscreen smartphones with software keyboards has, at least for the time being, tilted the balance of telecommunications in favor of typed rather than spoken messages (Shropshire 2015). Combined with the data provided by a phone's accelerometer, gyroscope, and screen pressure sensors, keystroke dynamics can be used to build mathematical models of a person's mood and cognition based only on how, and not what, they type.

Voice itself, of course, remains a valuable instrument for gaining insight into the speaker's mood state, and will only continue to become more so as the tide eventually turns toward speech-based interactions with both intelligent voice assistants and other human users of connected devices. Using similar statistical modeling and machine learning techniques, the acoustic features of speech are just as well-suited for analysis as typing kinematics (Cummings and Schuller 2019).

As more and more computing comes to be offloaded from personal devices to Internet of Things (IoT) devices and the cloud, and ambient computing becomes the norm, we expect that techniques like keystroke analysis will be supplanted by speech meta-feature analysis, facial emotional recognition (for more information on FER software, see Chap. 3 by Wilhelm and Geiger in this book), and altogether novel passive mood sensing tools. For the present time, being aware of the increasing ubiquity of algorithms and their influence on data analytics, digital architectures and digital societies (Dixon-Román 2016), as well as mindful of the absence of a codified analog for the Hippocratic Oath in the current practice of artificial intelligence in medicine as well as other applications (Balthazar et al. 2018), we nevertheless stand to learn a great deal from leveraging currently used input methods to derive models for sensing users' inner states.

13.2 Mobile Typing Kinematics

In the first known study of its kind, researchers from the University of Illinois at Chicago (UIC), the University of Michigan, the Politecnico di Milano, Tsinghua University and Sun Yat-sen University used passively obtained mobile keyboard usage metadata to predict changes in mood state with significant degrees of accuracy. The team recruited subjects from the Prechter Longitudinal Study of Bipolar Disorder at the University of Michigan as part of the BiAffect-PRIORI consortium for its pilot study based on an Android mobile keyboard and associated app. After winning the grand prize in the Mood Challenge supported by Apple and sponsored by the New Venture Fund of Robert Wood Johnson Foundation, UIC is currently conducting a full-scale study on the iOS platform using an app based on the open source ResearchKit mobile framework, enrolling both people with bipolar disorder as well as healthy controls from the general population.

The BiAffect study (https://www.biaffect.com/) involves the installation of a companion app containing a custom keyboard that is cosmetically similar to the stock system keyboard. The app includes mood surveys; self-rating scales; and active tasks such as a the go/no-go task and the trail-making test (part B) to measure reaction time, response inhibition, and set-shifting as part of executive functioning—all overlapping domains of cognition identified by Bourne and colleagues (2013) to be the most affected in bipolar disorder.

All data collected by the app and keyboard are first encrypted and then transmitted and stored on secure study servers; these were hosted at UIC for the Android pilot app, whereas study management services are being supported by Sage Bionetworks for the ongoing iOS study with the data being hosted on their Synapse platform. The Android pilot phase, which has concluded data collection, involved the keyboard, trail making test, Hamilton Depression Rating Scale (HDRS), Young Mania Rating Scale (YMRS), and slider-based daily self-rating scales for mood, energy, impulsiveness, and speed of thoughts; the main iOS study included each of these [with the notable substitution of the clinician-rated HDRS and YMRS with the self-reported Patient Health Questionnaire (PHQ) and the Altman Mania Rating Scale, respectively] as well as a daily self-rating scale querying ability to focus, and the aforementioned reaction time task. Metadata collected for keyboard usage include timestamps associated with each keystroke, residence time on each key, intervals between successive keystrokes, and accelerometer readings over the course of all active typing sessions. The actual character corresponding to any given keypress is not recorded, apart from noting whether it was a backspace, alphanumeric, or symbol key. In addition to backspace usage, instances of autocorrection and autosuggestion invocations are also logged.

Table 13.1 summarizes the literature that has been published thus far based on analyses of data collected during the pilot phase of the study, which included 40 participants—between 9 and 20 of whose data were used for any given one depending on the number of days of metadata logged, diagnosis of the participant, and other requirements; up to 1,374,547 keystrokes and 14,237,503 accelerometer readings

Table 13.1 A summary of analyses published by researchers using data from the BiAffect study

Author	Analytical technique	Predictors used	Main findings
Zulueta et al. (2018)	Linear mixed-effects models *(Preferred over ANOVA in settings where measurements are made on clusters of related statistical units due to advantages in dealing with missing values)*	Average inter-key delay, backspace ratio, autocorrect rate, circadian baseline similarity, average accelerometer displacement, average session length, and session count	Keystroke activity was predictive of depressive, and to a lesser extent, manic symptoms. Specifically, accelerometer displacement, average inter-key delay, session count, and autocorrect rate were positively correlated with the HDRS scores, whereas accelerometer displacement was positively correlated and backspace rate negatively correlated with YMRS scores
Stange et al. (2018)	Multilevel models to evaluate predictiveness of instability metrics computed using the root mean square successive difference *(Specific models for each level of multilevel data, thereby modeling the non-independence of observations due to cluster sampling)*	Instability of EMA affective ratings and daily typing speed	Greater instability of mood during baseline EMA was predictive of future depressive symptoms, while instability of energy predicted future manic but not depressive symptoms. Instability of typing speed predicted prospective depressive but not manic symptoms. Models built using data gathered during only 5–7 days were as reliable and predictive as those assessing instability over longer time periods
Cao et al. (2017)	Comparison of late fusion based DeepMood LSTM-type GRU ML architecture with a multi-view RNN machine layer, factorization machine layer, or conventional fully connected layer against early fusion approaches *(Recurrent connections between machine learning layers allow modeling of nonlinear time series that, after training on sufficient data, can solve problems with prolonged temporal dependencies, such as linguistic, semantic, and topic inference tasks.)*	Multiple representative views of the features of each typing session such as alphanumeric characters, special characters, and accelerometer values	Healthy people showed a wider range of variability in the time intervals between successive alphanumeric keypresses than people who were experiencing a mood disturbance. People in a manic state tend to hold down a keypress longer than people in a stable mood state, while depressed people pressed down on keys for shorter than average durations. The DMVM and DFM based architectures were the most predictive of depression scores, with prediction performances of 90.31% and 90.21%, respectively

(continued)

Table 13.1 (continued)

Author	Analytical technique	Predictors used	Main findings
Huang et al. (2018)	dpMood ML architecture based on early fusion, stacked CNNs to capture local typing dynamics and RNNs to capture temporal dynamics, and final predictions based on individual circadian calibrations *(More typically employed in computer vision models, CNNs outperform shallow architectures when predicting mental health related aspects from multiple data streams, while reaching at least comparable performance levels as predesignated architectures.)*	Metadata for alphanumeric characters, including duration of keypress, time since last keypress, distance from the center of the last pressed key along both axes, and corresponding accelerometer values during active sessions	The proposed dpMood architecture incorporating CNNs, RNNs, early fusion and time-based calibration taken together outperformed any individual approach alone or in combination with just a few others. The integrated analysis of local patterns and temporal dependencies allowed for the isolation of variations in keyboard usage at different times of the day and from day to day over the course of the week, and the personalized calibration was sensitive enough to be able to distinguish between healthy controls and subjects with type I and type II bipolar disorder
Vesel et al. (2020)	Growth curve mixed-effects (multilevel) models in R and lme4 using maximum likelihood fitting *(R version 3.6.1; R Foundation for Statistical Computing, Vienna, Austria; lme4 version 1.1-21)*	Examined dependent variables of session-level typing speed, typing variability, typing accuracy, and session duration and their relationship to other session-level features and demographics	More severe depression relates to more variable typing speed ($P < 0.001$), shorter session duration ($P < 0.001$), and lower accuracy ($P < 0.05$). Additionally, typing speed and variability exhibit a diurnal pattern, being fastest and least variable at midday. Older users exhibit slower and more variable typing, as well as more pronounced slowing in the evening. The effects of aging and time of day did not impact the relationship of mood to typing variables
Ross et al. (2021)	Longitudinal mixed-effects models (with maximum likelihood estimator fitting) were used to analyze daily digital trail-making test, part B (TMT-B) performance as a function of typing and mood *(All analyses were conducted in R version 3.6.3; R Core Team 2020)*	Keypress metadata, paper and digital TMT-B completion times, and Hamilton Depression Rating Scale scores	Participants who typed slower took longer to complete dTMT-B, with this trend also being seen in individual fluctuations in typing speed and dTMT-B performance. Participants who were more depressed completed the dTMT-B slower than less depressed participants

(continued)

Table 13.1 (continued)

Author	Analytical technique	Predictors used	Main findings
Zulueta et al. (2021)	Two random forest regression models were trained using the caret and randomForest packages for R *(All statistical testing was performed in R version 4.0.0)*	Features derived from the smartphone kinematics were used to train random forest regression models to predict age	Smartphone kinematics were successfully used to predict chronological age. The absolute prediction error tended to be lower for participants with positive screens than those with negative screens, whereas the raw prediction error tended to be lower for participants with negative screens than those with positive screens

Abbreviations *EMA* ecological momentary assessment; *HDRS* Hamilton Depression Rating Scale; *YMRS* Young Mania Rating Scale; *LSTM* long short-term memory; *GRU* gated recurrent unit; *ML* machine learning; *DMVM* DeepMood multi-view machine; *DFM* DeepMood factorization machine; *DNN* DeepMood neural network; *CNN* convolutional neural network; *RNN* recurrent neural network

across 37,647 sessions were incorporated into some of the resulting models. Data collection for the main arm of the study is ongoing and has already resulted in over 8000 cumulative hours of active typing sessions culled from across hundreds of users.

Zulueta and colleagues (2018) built mixed-effects linear models to correlate keyboard activity metadata during the week preceding when each pair of mood rating scales was administered to the corresponding HDRS and YMRS scores. A representative sampling of these metadata over several weeks from one study participant is illustrated in Fig. 13.1, while Fig. 13.2 compares the scores predicted by these models against actual scores for both mood scales. Autocorrect rates were positively correlated with depression scores, probably because error-awareness becomes impaired when depressed (Fig. 13.3a). Backspace usage rate was found to be negatively correlated with higher mania scores, possibly because it is reflective of decreased self-monitoring and impaired response inhibition (Fig. 13.3b). Accelerometer activity was positively correlated with both depression and mania scores, possibly because study subjects were experiencing depression with mixed features or agitated/irritable depression. The trail making test, which consists of circles with alternating consecutive numbers and/or letters that respondents are directed to connect in the correct order, is a standard neuropsychological assessment that measures processing speed and task-switching, which are both good indicators of cognitive functioning; Fig. 13.4 shows how typing kinematics data were just as predictive as trail making test results at establishing cognitive ability.

Stange et al. (2018) took a different approach by constructing multilevel models based on instability metrics calculated for EMA ratings and daily typing speeds (Fig. 13.5) using the root mean square of the successive differences (rMSSD)—a time-domain measure that takes into account the magnitude, frequency, and temporal order of intra-user fluctuations (Ebner-Priemer et al. 2009). Greater instability in baseline mood EMA ratings was significantly predictive of elevated future symptoms of both depression (Fig. 13.6a) and mania, whereas instability in energy ratings

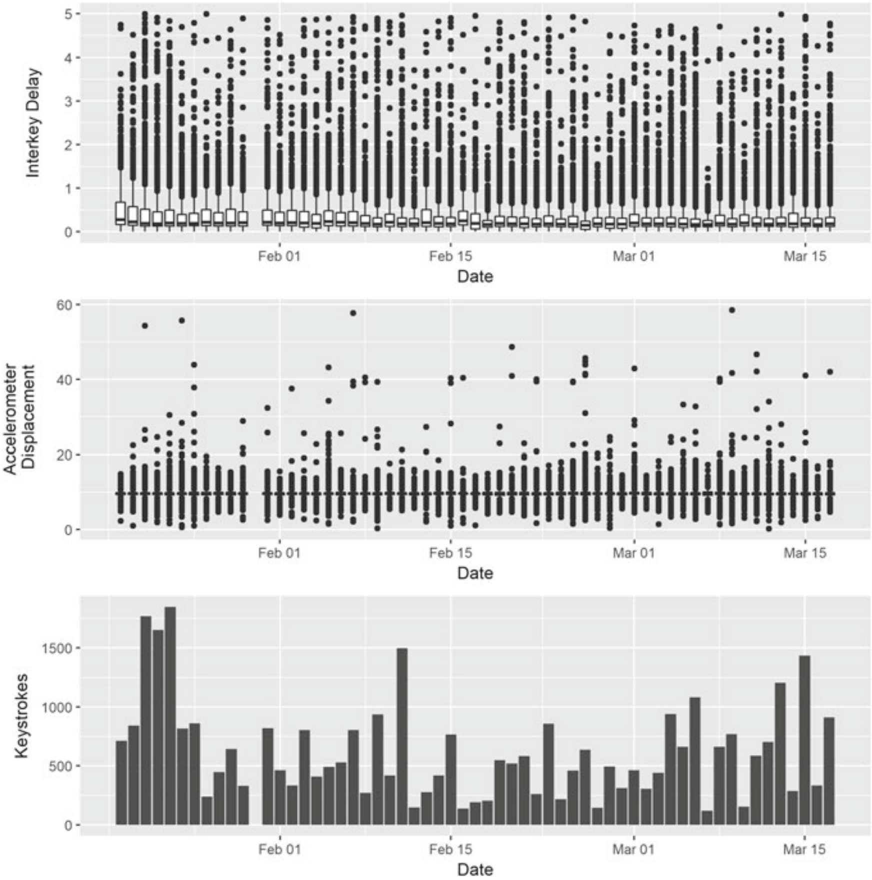

Fig. 13.1 An example of the deep personalized sensing possible with BiAffect showing the number of keystrokes, corresponding accelerometer readings, and the time between successive keypresses logged for an individual participant over the duration of the pilot study phase. Adapted from Zulueta et al. (2018)

was predictive of future mania but not depression; other affective EMA ratings were not found to be significantly predictive of either. Typing speed instability was predictive of elevated prospective symptoms of depression (Fig. 13.6b) but not of mania. Interestingly, as little as one week of data provided levels of predictiveness comparable to data collected over durations of time longer than 5–7 days, perhaps because this time period is a representative enough snapshot to capture day-to-day typing variability (Fig. 13.7). Turakhia and colleagues (2019) have subsequently gone on to demonstrate the feasibility of exploiting variability in similar irregular noncontinuous datastreams to identify, predict, and prevent potential serious episodes—atrial flutters and fibrillations in the case of their app- and wearable-based study on cardiac arrhythmia.

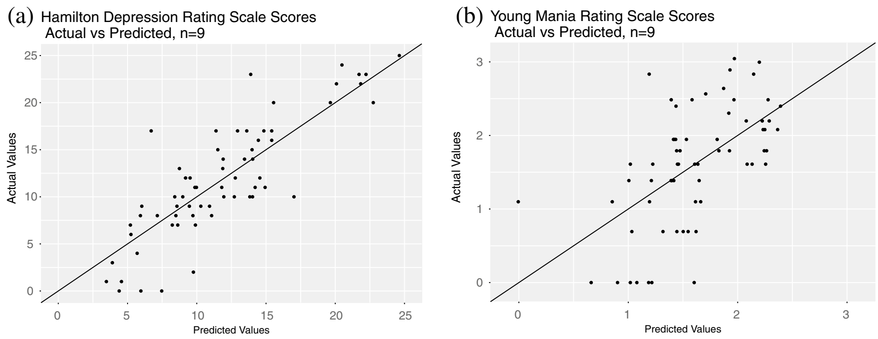

Fig. 13.2 Mixed effects modeling accounted for 63% of the variability of Hamilton Depression Rating Scale scores (Conditional $R^2 = 0.63$, Marginal $R^2 = 0.41$, $\chi^2{}_7 = 17.6$, $P = 0.014$). Ordinary least squares modeling accounted for 34% of the natural log of Young Mania Rating Scale scores (Multiple $R^2 = 0.34$, Adjusted $R^2 = 0.26$, $F_{7,56} = 4.1$, $P = 0.0011$) Adapted from Zulueta et al. (2018)

Cao and colleagues (2017) were among the first to model keystroke dynamics data using deep learning. Their method, DeepMood, consisted of comparing the predictive performance of a multi-view machine layer architecture (Fig. 13.8) to that of other late fusion approaches such as factorization and conventional fully connected layers as well as early fusion strategies like tree boosting systems, linear support vector machines, and logistic ridge regression models. For the uninitiated, a review on current applications of deep neural networks in the field of psychiatry by Durstewitz et al. (2019) may serve as a primer. DeepMood's early fusion approaches align each of the data views—alphanumeric characters, special characters, and accelerometer values—with their associated timestamps (Fig. 13.9), and then immediately concatenate the multi-view time series per session. However, this does not take into proper account unaligned features in certain views, such as special characters, that do not have corresponding data points from other views like acceleration or inter-key distance. This shortcoming is addressed by the late fusion approach, in which each of the multi-view series is first modeled separately by a recurrent neural network (RNN), and then fused in the next stage by analyzing first-, second-, and third-order interactions between each view's output vectors. Cao and colleagues established that their late fusion approach significantly outperformed early fusion in the ability to predict mood disturbances and their severity (Fig. 13.10), with the multi-view machines demonstrating the highest rate of accuracy at 90.31% followed by the factorization machines at 90.21%.

In a subsequent analysis, Huang et al. (2018) found that an early fusion approach integrating both convolutional and recurrent deep architectures and incorporating users' circadian rhythms allowed their model, dpMood, to attain even greater predictive performance as well as make more precise personalized mood predictions that took into fuller account an individual's biological clock and unique typing patterns. Their approach consisted of using convolutional neural networks (CNNs)

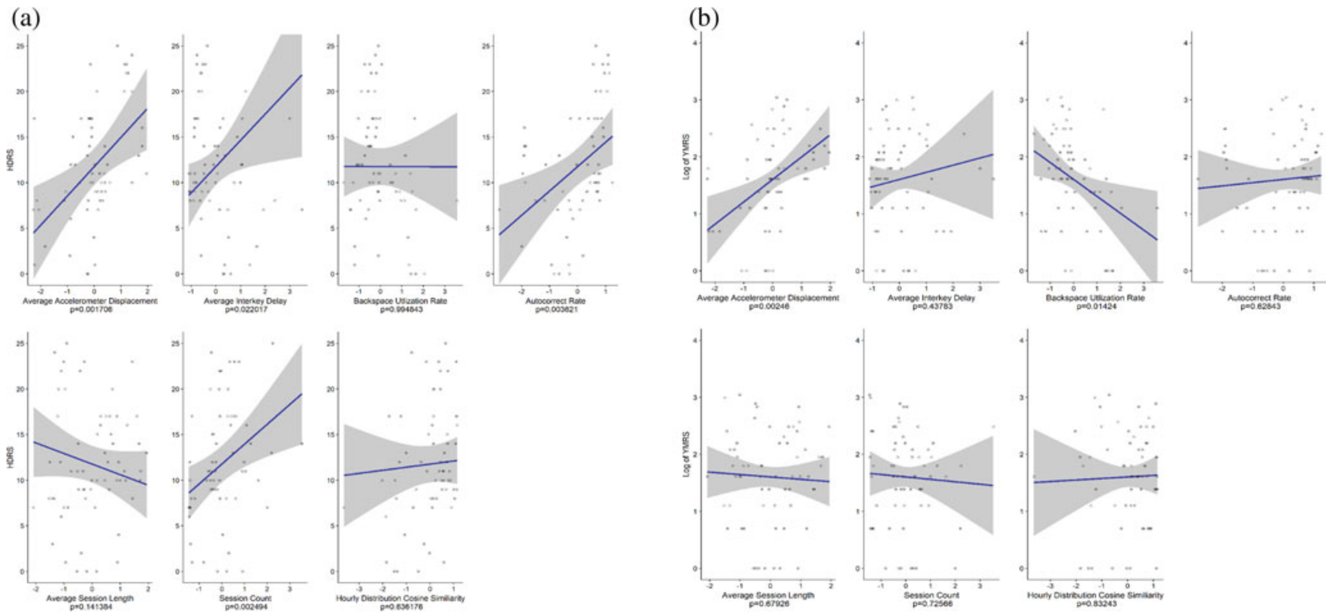

Fig. 13.3 Significant predictors for Hamilton Depression Rating Scale scores included accelerometer displacement ($P = 0.0017$), interkey delay ($P = 0.022$), autocorrect rate ($P = 0.0036$), and session count ($P = 0.0025$). Significant predictors for the natural log of the Young Mania Rating Scale scores include accelerometer displacement ($P = 0.003$) and backspace rate ($P = 0.014$). Adapted from Zulueta et al. (2018)

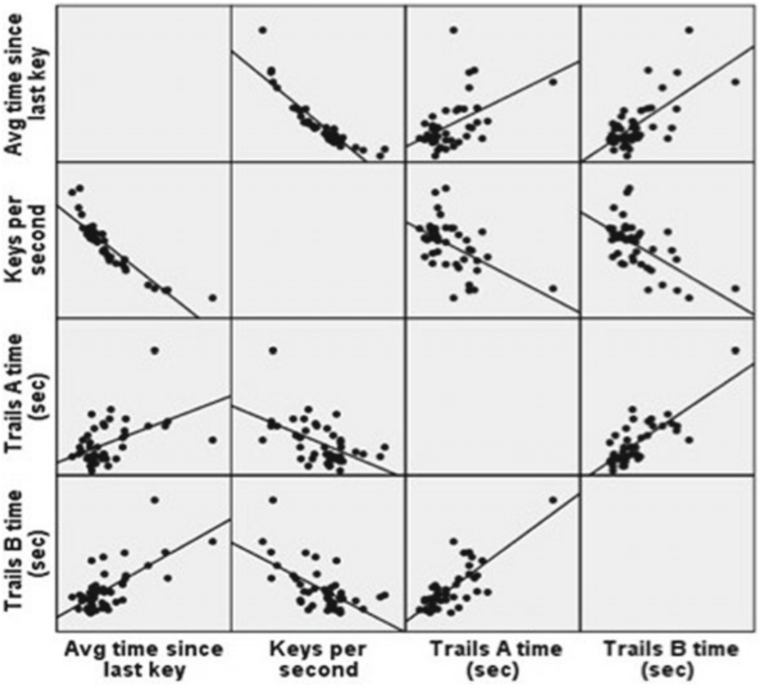

Fig. 13.4 Comparison of the predictiveness of keystroke data with that of trail making test results for assessing cognitive ability. Processing speed, as measured by trail taking test (part A) scores, was significantly correlated with average interkey delay (i.e., time since last key, $r = 0.5$, $p < 0.001$) and keys/second ($r = -0.54$, $p < 0.001$). Set shifting, as measured by trail taking test (part B) scores, was highly associated with average time since last key ($r = 0.68$, $p < 0.00001$) and keys/second ($r = -0.62$, $p < 0.00001$). Adapted from Zulueta et al. (2018)

that focused on temporal dynamics to analyze local features in typing kinematics over small periods of time, in conjunction with a special type of RNN called a gated recurrent unit (GRU) to model longer-term time-related dynamics (Fig. 13.11). GRUs address the vanishing gradient problem—the inherent inability of simpler RNNs to effectively learn those parameters that only cause very small changes in the neural network's output—and moreover have fewer parameters than comparable ameliorative approaches, allowing them to perform better on smaller datasets (Cho et al. 2014) such as the keystroke kinematics collected by BiAffect. This early fusion approach allowed for the alignment of features from multiple views to include additional information about temporal relationships between these data points that would otherwise be lost in late fusion models. In the final analysis, the proposed dpMood architecture with the best predictive performance and the lowest regression error rate was the one that made combined use of both CNNs and RNNs to learn local patterns as well as temporal dependencies, learned each user's individual circadian rhythm, and retained accelerometer values that had no contemporaneous alphanumeric keypresses by filling the unaligned alphanumeric features with zero values instead of dropping

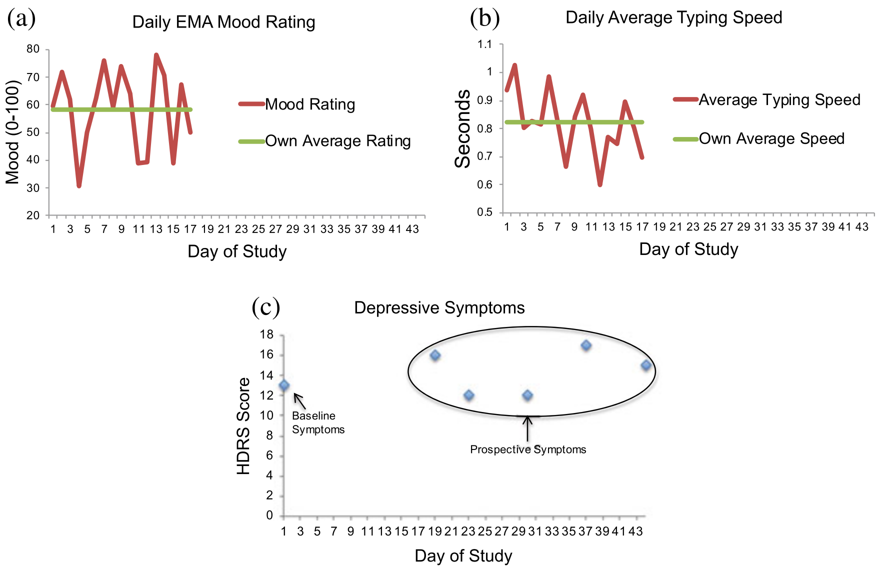

Fig. 13.5 An individual participant's a self-rated ecological momentary assessment scores, b passively collected daily typing speeds and c baseline and future course of depression symptom severity. Adapted from Stange et al. (2018) and reproduced with permission from the publisher

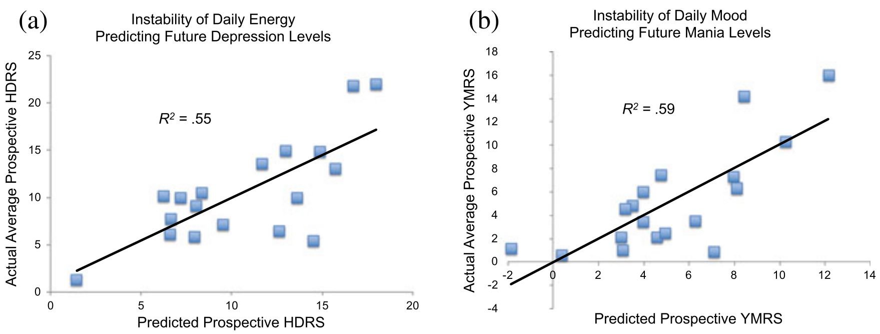

Fig. 13.6 Comparison of actual scores with those predicted by multilevel instability models for an individual participant's a Hamilton Depression Rating Scale and b Young Mania Rating Scale. Adapted from Stange et al. (2018) and reproduced with permission from the publisher

unaligned accelerometer values altogether. Accelerometric and time-based analyses elucidated both daily (Figs. 13.12 and 13.13) and hourly (Fig. 13.14) variations in keyboard use, with the notably smaller Z-axis accelerations that help pinpoint when a phone is being typed on from a supine position having been observed more predominantly in the evenings (Fig. 13.14c) and on weekends (Fig. 13.13d). Modeling individuals' circadian rhythms as a sine function with parameters automatically learned by gradient descent algorithms and backpropagation resulted in one of

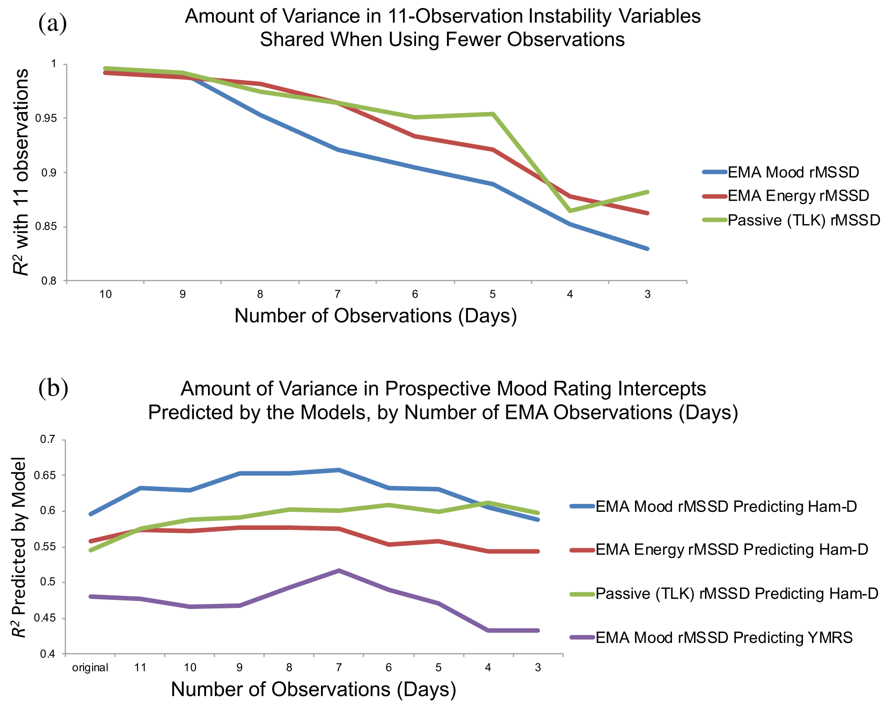

Fig. 13.7 **a** Reliability of active and passive assessments of instability depending on number of days of assessment. **b** Predictive utility of active and passive assessments of instability depending on number of days of assessment. Adapted from Stange et al. (2018) and reproduced with permission from the publisher

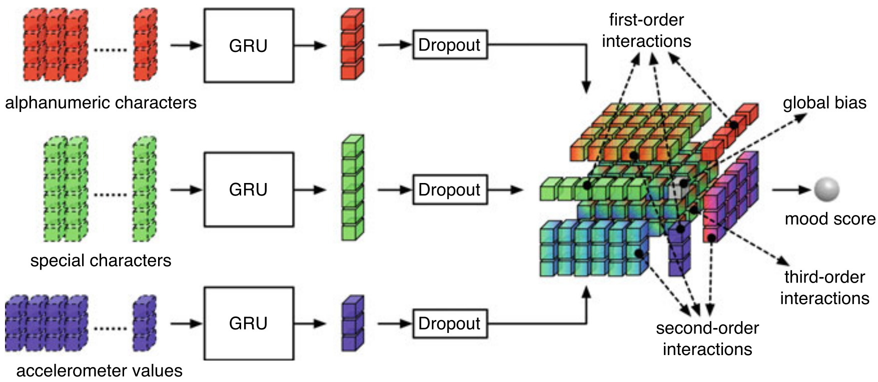

Fig. 13.8 DeepMood machine learning architecture with a multi-view machine layer for late data fusion. Adapted from Cao et al. (2017)

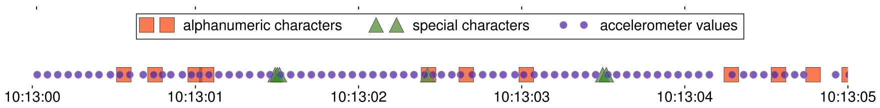

Fig. 13.9 A representative sample of the multi-view metadata collected in a time series. Adapted from Cao et al. (2017) and reproduced with permission from the publisher

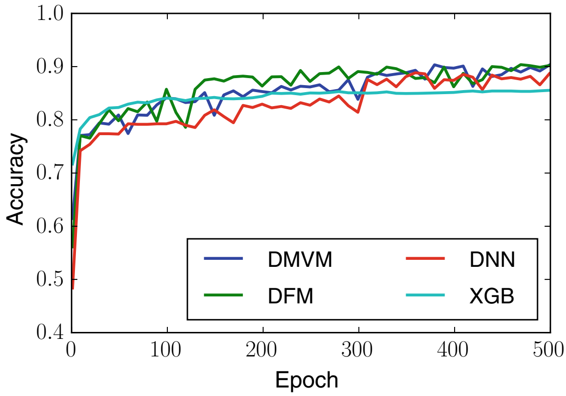

Fig. 13.10 Comparison of the improvements in accuracy of different DeepMood architectural approaches over the course of successive training epochs. Adapted from Cao et al. (2017) and reproduced with permission from the publisher

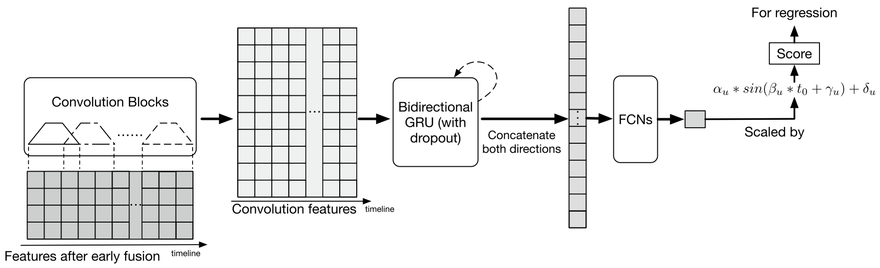

Fig. 13.11 dpMood machine learning architecture based on early data fusion stacked CNNs and GRUs, and time-based calibrations.Adapted from Huang et al. (2018) and reproduced with permission from the publisher

these parameters conspicuously clustering based on the subjects' diagnoses, permitting dpMood to successfully classify users as participants with bipolar I disorder, those with bipolar II disorder, or healthy controls (Fig. 13.15). These sophisticated techniques can combine to provide extraordinarily insightful mood-sensing tools to users and precision medicine practitioners alike.

Preliminary analysis of study participants' performance on the go/no-go task has indicated that reaction times vary both within and between individuals (Fig. 13.16a) as well as continue to change over time (Fig. 13.16b); variations in daily typing patterns in BiAffect users have been found to correlate with their performance on the

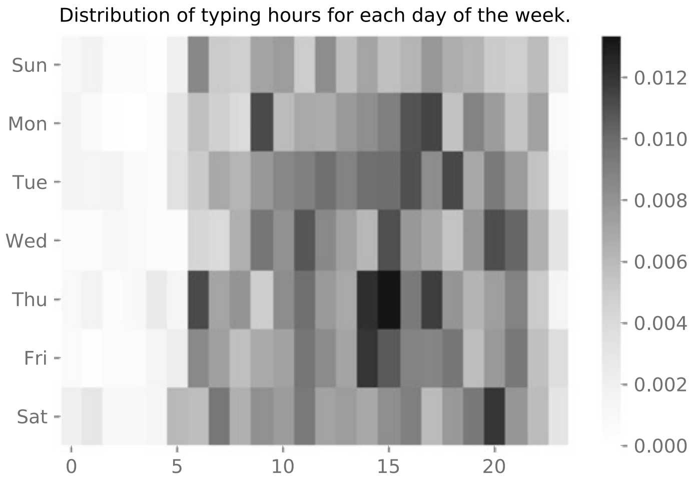

Fig. 13.12 Distribution of daily typing hours visualized as a 7 day × 24 h matrix. Adapted from Huang et al. (2018) and reproduced with permission from the publisher

go/no-go task, and concurrent analyses of both data streams are now under way to examine their interrelationships and interactions with mood and cognition as well.

Vesel and colleagues (2020) investigated the effects of mood, age, and diurnal patterns on intraindividual variability (IIV) in typing behaviors recorded in the iOS dataset, correlated against participants' responses to the PHQ. Interkey delay (IKD) was calculated as the time difference between 2 consecutive keypresses and analysis was restricted to only IKDs between character-to-character keypress events; typing speed of a session was operationally inferred using the median IKD of that session. Typing variability at the session level was quantified using the median absolute deviance of IKDs. Typing mode (the use of one or two hands when typing) was classified using a novel approach utilizing linear regression. Growth curve mixed-effects (multilevel) models were established using maximum likelihood fitting to examine dependent variables of session-level typing speed, typing variability, typing accuracy, and session duration and their relationship to other session-level features and demographics (Fig. 13.17).

It was established that typing speed exhibits slowing with age, while pausing between typing and variability in typing speed increase with age. The relationship between keystroke dynamics features and mood was supported by the significantly higher variability in IKDs observed with more severe depression, consistent with reported findings of higher IIV in task performance in mood disorders. Typing accuracy, as encoded using session-level autocorrect rates, was also found to decrease in more depressed individuals. Finally, sessions corresponding to elevated depressive symptoms were found to be shorter in duration, suggesting a decrease in smartphone keyboard use during more severe depression.

Ross et al. (2021) evaluated the efficacy of using smartphone typing dynamics along with mood scores in cognitive assessment as an adjunct to formal in-person

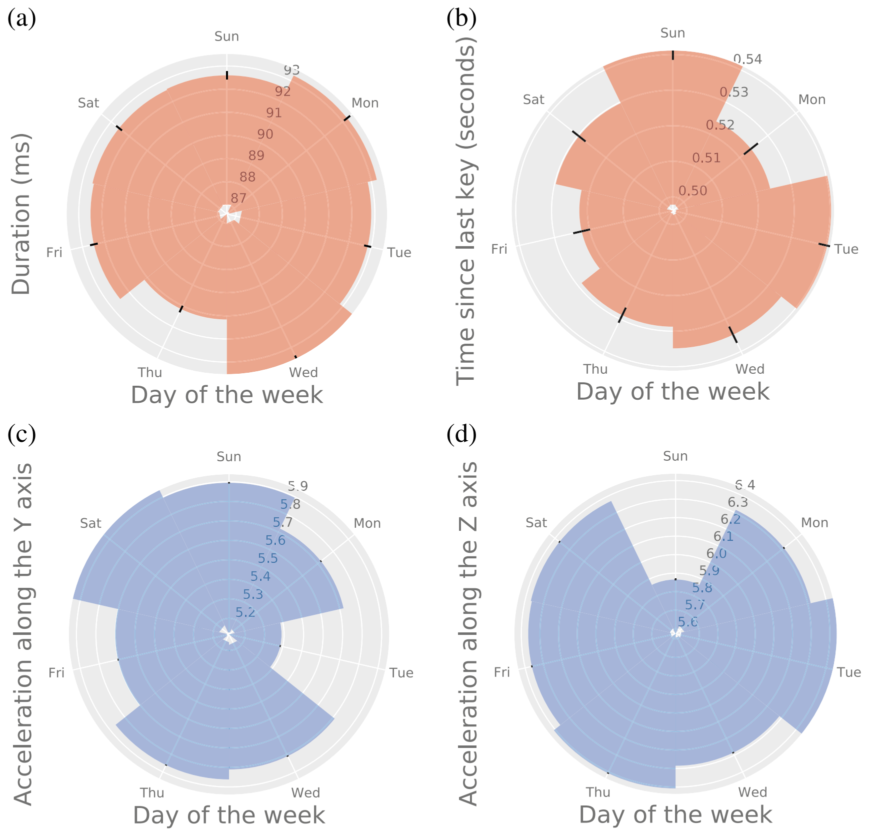

Fig. 13.13 Day-to-day fluctuations over the course of a week in a duration of a keypress, b time between successive keypresses, c acceleration along Y-axis, and d acceleration along Z-axis. Adapted from Huang et al. (2018) and reproduced with permission from the publisher

neuropsychological assessments through trail making tests. In addition to using the Android pilot app keyboard, participants were administered the pencil-and-paper version of the trail-making test, part B (pTMT-B) at the beginning and end of the study, as well as completed digital TMT-Bs (dTMT-B) throughout the study on their smartphones, and responded to the Hamilton Depression Rating Scale (HDRS) and Young Mania Rating Scale (YMRS) over the course of weekly phone interviews. For analysis, time windows were selected such that each consisted of one dTMT-B, one HDRS-17 score, and multiple keypresses, as shown in Fig. 13.18.

Intraclass correlations between the digital and paper-based forms of TMT-B were calculated to assess the consistency between both modalities. Comparison of the first dTMT-B to paper TMT-B showed adequate reliability. Longitudinal mixed-effects models were then used to analyze daily dTMT-B performance as a function of typing and mood. Participants who typed slower were observed to take longer to complete

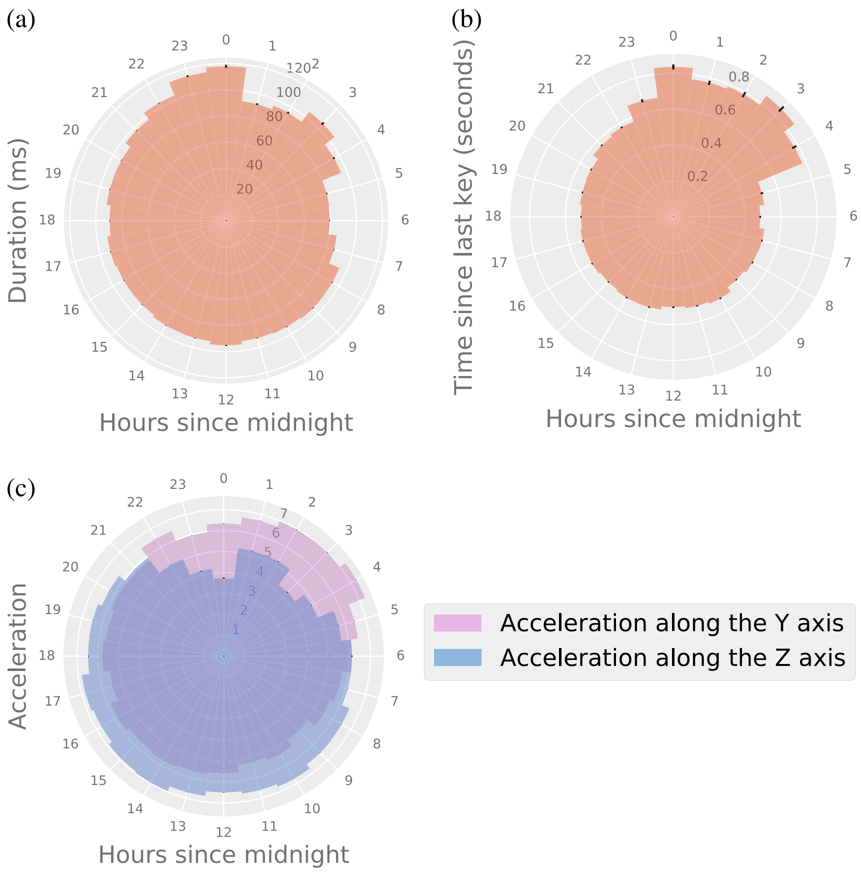

Fig. 13.14 Circadian rhythm mediated fluctuations in a duration of a keypress, b time between successive keypresses, and c acceleration along Y- and Z-axes. Adapted from Huang et al. (2018) and reproduced with permission from the publisher

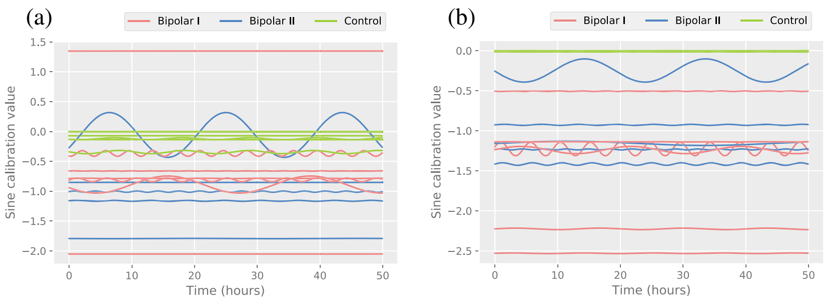

Fig. 13.15 Visualizations of each individuals' calibration sine functions for a Hamilton Depression Rating Scale scores and b Young Mania Rating Scale scores. Adapted from Huang et al. (2018) and reproduced with permission from the publisher

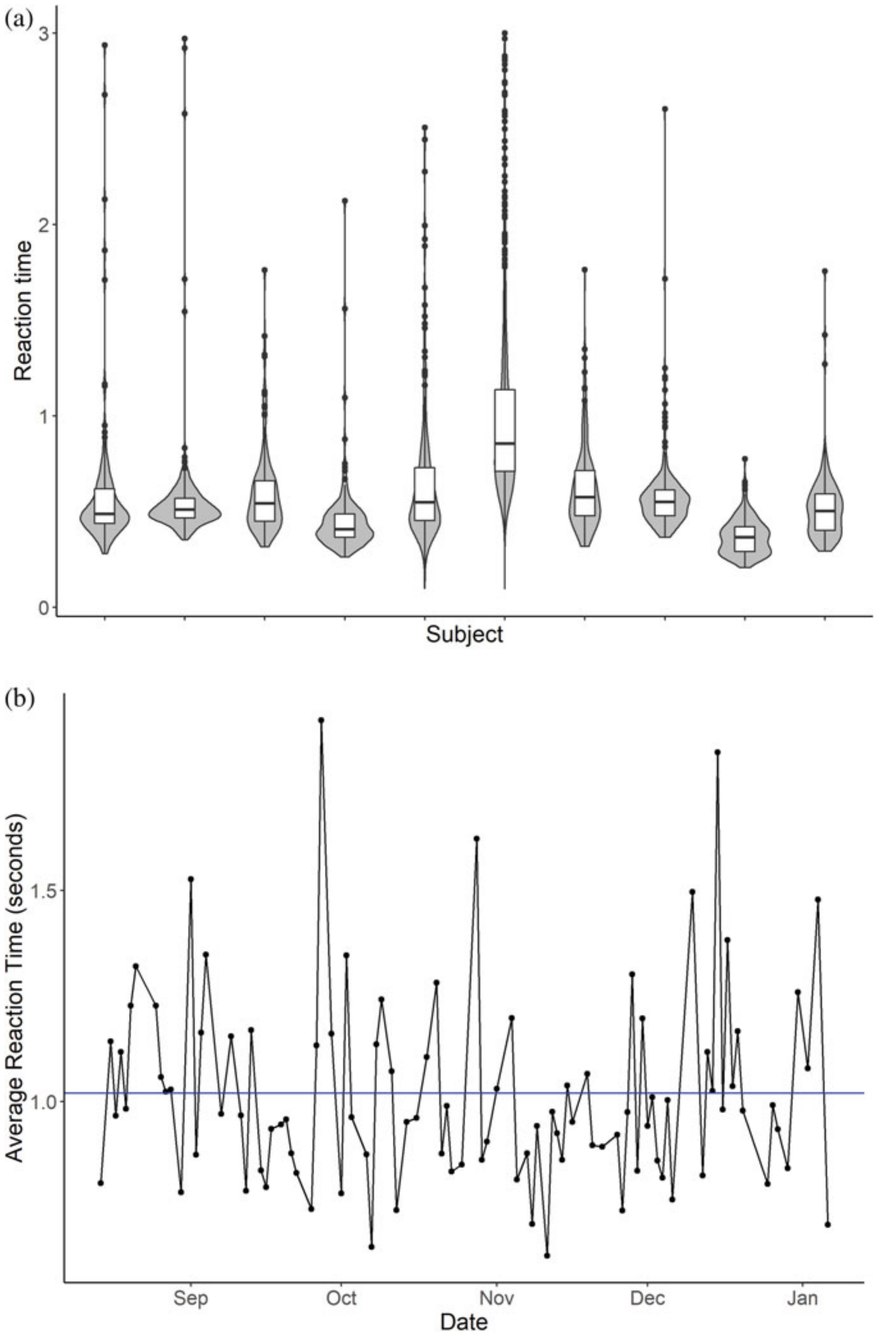

Fig. 13.16 A Go/no-go reaction time varies between and within individuals. b Average reaction time changes over the course of time

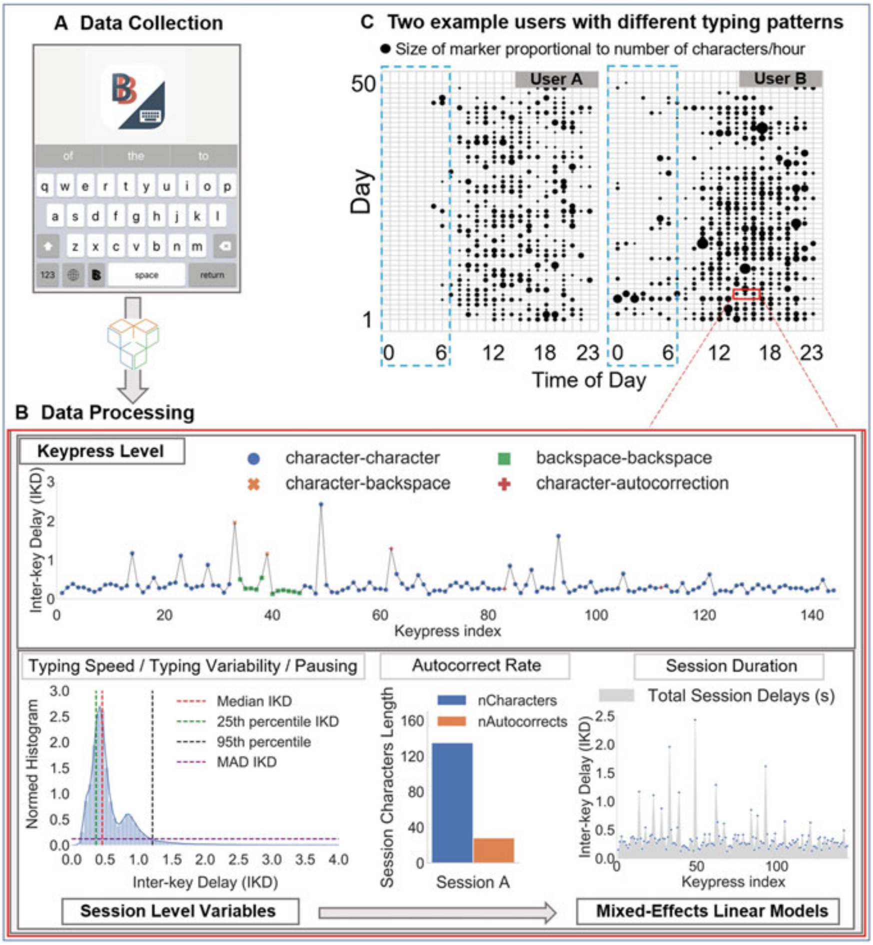

Fig. 13.17 Overview of BiAffect data collection and feature extraction process. **a** Keypress-level typing metadata are collected via the BiAffect keyboard and stored by Sage Bionetworks. **b** Interkey delays for keypress transitions from character to character are aggregated at a session level to compute median absolute deviance alongside typing accuracy and session duration. **c** An example for the hourly typing activity over multiple days from 2 active users is presented as an illustration of the potential patterns captured via continuous, unobtrusive collection. The blue dashed line highlights the different levels of activity at night, with user B exhibiting a more irregular activity pattern than user A. Size of the marker is proportional to the number of characters typed per hour

dTMT-B. This trend was also seen in individual fluctuations in typing speed and dTMT-B performance (Fig. 13.19). Moreover, participants who were more depressed completed the dTMT-B slower than less depressed participants (Fig. 13.20).

Depression severity was associated with the dTMT-B time at both the inter- and intrasubject level. Participants who were more depressed completed dTMT-B more slowly than participants who were not depressed. Typing speed was also associated

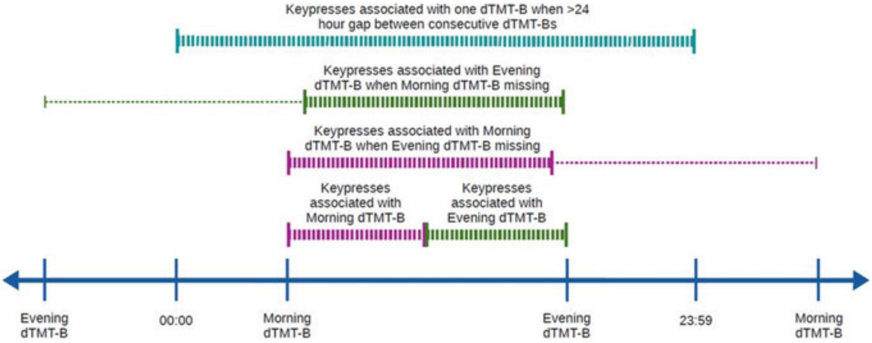

Fig. 13.18 Schematic outlining how keypresses were assigned to each digital trail making test part B (dTMT-B) to account for missing data

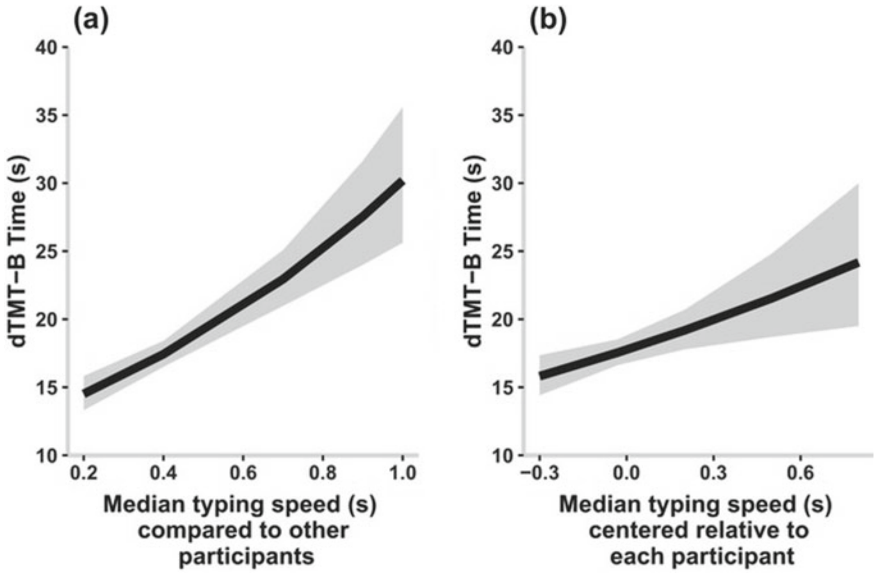

Fig. 13.19 Digital trail-making test part B completion time as a function of grand mean centered (**a**) and subject centered (**b**) typing speed with ribbons showing the 95th confidence interval

with the dTMT-B at both inter- and intrasubject levels. Faster typists completed the dTMT-B more quickly than slower typists. Participants' individual fluctuations in typing speed reflected their fluctuations in dTMT-B over the course of the study. A diagnosis of bipolar disorder was found to be a significant predictor of dTMT-B completion time, after controlling for depression score and typing speed.

Zulueta et al. (2021) analyzed participants' responses to the Mood Disorders Questionnaire (MDQ) and self-reported birth year against Features derived from the smartphone kinematics, which were used to train random forest regression models

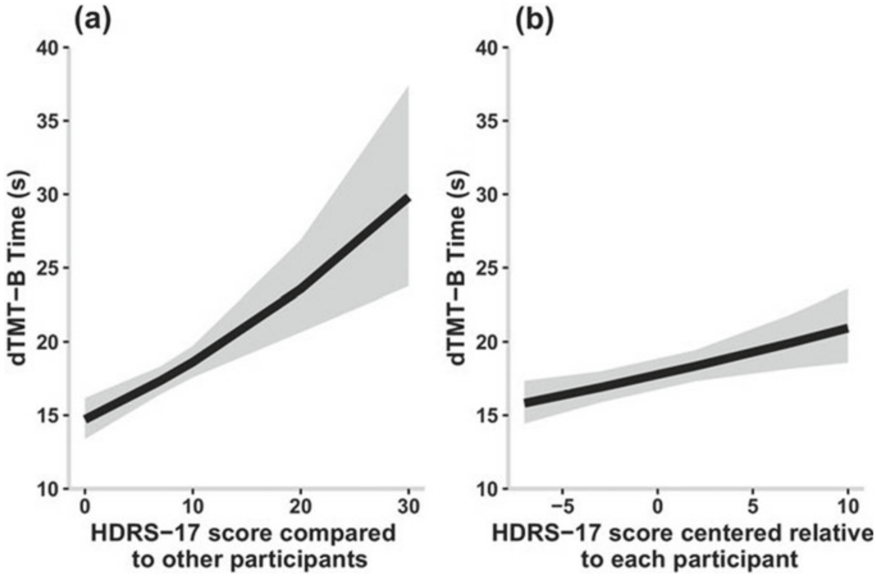

Fig. 13.20 Digital trail-making test part B completion time as a function of grand mean centered (**a**) and subject centered (**b**) Hamilton Depression Rating Scale score with ribbons showing the 95th confidence interval

to predict age. Data were split into training and validation sets (75:25). Two random forest regression models were trained using the caret and randomForest packages for R. The mtry value which minimized the Root Mean Square Error (RMSE) was selected as the value used in the final models. The models were constructed in a stepwise fashion with the first model including only typing related features, and the second model included all features from the first with the addition of gender and MDQ screening status. Each model's performance was assessed using the validation set to calculate RMSE, Breiman's pseudo R-squared, and median absolute error. Differences in model performance testing were assessed using paired Wilcoxon tests of their absolute errors. Feature importance was assessed using out-of-bag changes in Mean Square Error (MSE). Accumulated Local Effects plots (ALE Plots) were constructed for features which appeared important or interesting. Differences within model performance between participants based on MDQ screen status were assessed using Wilcoxon tests comparing raw prediction error scores and absolute prediction error scores.

Compared to participants with positive MDQ screens, participants with negative screens had a lower rate of reporting a diagnosis of bipolar disorder, a higher rate of reporting no history of bipolar disorder, and also provided no diagnosis history at a lower rate. The participants with negative screens tended to have lower MDQ scores comparted to those with positive screens and have a greater total number of keypresses. Plots A–D of Fig. 13.21 depict the ALE plots of four of the most important features: the median of mean interkey times, the mean session length, the

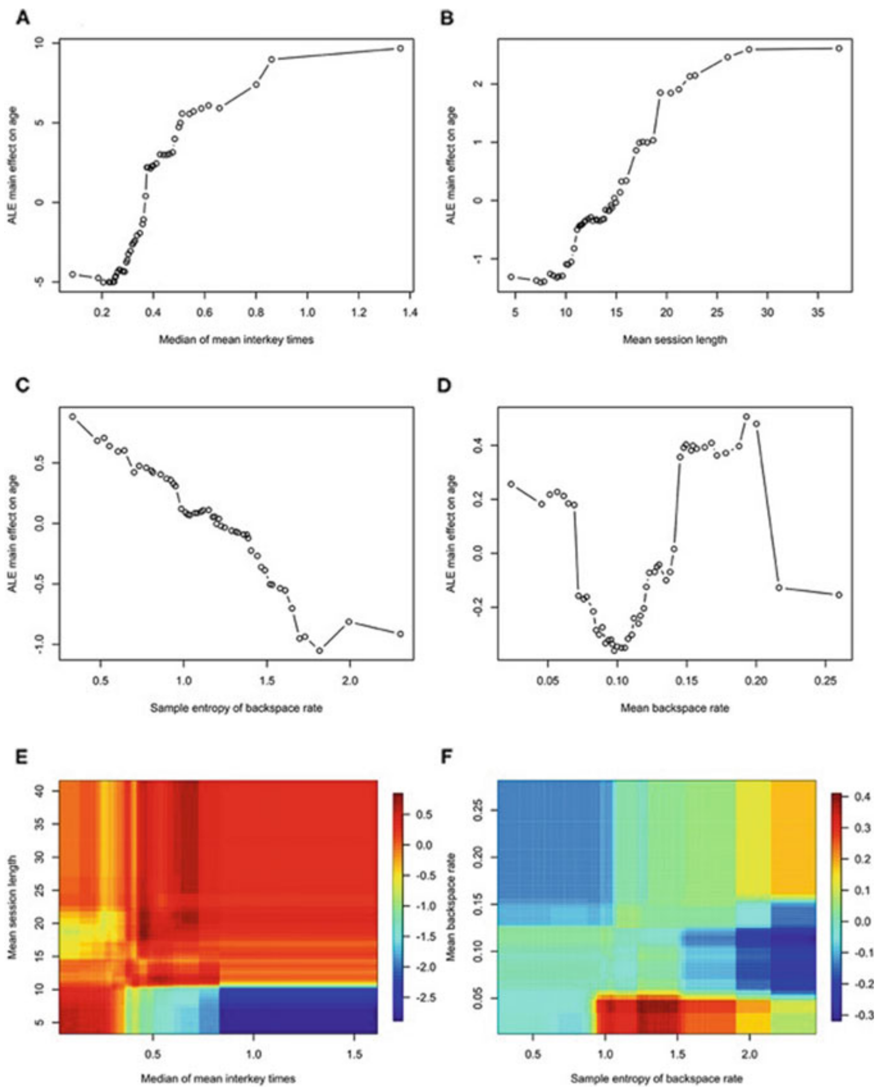

Fig. 13.21 Accumulated Local Effects plots for the second model. **a**–**b** Depict the effects of individual features on age prediction. **e**, **f** depict the interaction of the two indicated effects on age

sample entropy of the backspace rate, and the mean backspace rate. Many of the most important features are different summaries of the same essential feature (e.g., interkey time). Based on these plots, increased interkey time and session length are both generally associated with increased age; whereas, increased sample entropy of the backspace rate is associated with younger age, and the association between age and the mean backspace rate is not monotonic. Plots E and F of Fig. 13.21 depict the interaction between the median of mean interkey times and the mean session length and between the mean backspace rate and the sample entropy of the backspace rate, respectively. In these plots, it is observed that the existence and directionality of linear trends between the predicted age and these features both depend on the range of a second associated feature, highlighting the complexity of the relationship between typing behaviors and predicted age.

The tendency to underestimate the chronological age of participants screening negative for bipolar disorder compared to those screening positive is consistent with the finding that bipolar disorder may be associated with brain changes that could reflect pathological aging. This interesting result could also reflect that those who screen negative for bipolar disorder and who engaged in the study were more likely to have higher premorbid functioning. This work demonstrates that age-related changes may be detected via a passive smartphone kinematics based digital biomarker.

13.3 Speech Dynamics

Research on keystroke kinematics was inspired by the work of colleagues at the University of Michigan's Heinz C. Prechter Bipolar Research Program on the Predicting Individual Outcomes for Rapid Intervention (PRIORI) project, which is based on analyzing voice patterns in participants enrolled in the longest longitudinal research study of bipolar disorder; BiAffect aims to infer mood from typing metadata just as PRIORI does from the acoustic meta-features of speech. Participants were enrolled in the PRIORI study for an average of 16 to 48 weeks and were provided a rooted Android smartphone with a preinstalled secure recording application that captured audio of the participant's end of every phone call. Study staff called participants weekly to administer HDRS and YMRS mood assessments; these calls were labeled separately from personal calls. The dataset has accumulated over 52,000 recorded calls totaling above 4,000 h of speech from 51 participants with bipolar disorder and 9 healthy controls.

Karam et al. (2014) used a support vector machine (SVM) classifier to perform participant-independent modeling of segment- and low-level features extracted by the openSMILE audio signal processing toolkit, and were able to separate euthymic speech from hypomanic and depressed speech using an average of 5 to 8 judiciously selected features. In a later study, Gideon et al. (2016) used a declipping algorithm to approximate the original audio signal, and performed noise-robust segmentation to improve inter-device audio recording comparability. Rhythm features were classified using multi-task SVM analysis, then transformed into call-level features, and finally Z-normalized either globally or individually by subject. Declipping and SVM classification was found to increase the performance of manic but not depressive predictiveness, whereas segmentation and normalization significantly increased both. Khorram et al. (2016) captured subject-specific mood variations using i-vectors, and utilized a speaker-dependent SVM to classify both these i-vectors as well as rhythm features. Fusion of the subject-specific model—using unlabeled personal calls—with a population-general system enabled significantly improved predictive performance for depressive symptoms compared to the earlier approach used by Gideon and colleagues (2016). Khorram et al. (2018) went on to develop an ‘in the wild’ emotion dataset collating valence and activation annotations made by human raters drawing only upon the acoustic characteristics, and not the spoken content, of recordings from both personal and assessment calls.

Ongoing analyses, confounding challenges, and proposed solutions related to voice analysis have been outlined in a concise review by the PRIORI team (McInnis et al. 2017); their current focus is to isolate elements in the speech signal that are most strongly correlated with incipient disturbances in mood, enabling the development of on-device analytical systems without compromising limited mobile phone battery life.

13.4 Future Directions

The eventual goal of these projects is to be able to generate an early warning signal when changes in users’ patterns of typing, speech, and behavior identify them to be at risk for an imminent manic or depressive episode. This would allow for just-in-time adaptive interventions that can circumvent or at least minimize the acuteness of the episode and any resulting cases of hospitalization, medication adjustment, or self-harm (Rabbi et al. 2019).

It has not escaped our attention that these passive sensing techniques can have applications in conditions other than bipolar disorder and indeed beyond just mood disorders; we have been investigating the use of a voice-enabled intelligent agent that are responsive to users’ mood in order to provide emotionally aware education and guidance to patients with comorbid diabetes and depression (Ajilore 2018), as well as exploring the effectiveness of keystroke dynamics modeling in disparate conditions ranging from neurodegenerative processes such as Alzheimer’s disease to cirrhotic sequelae such as hepatic encephalopathy.

The BiAffect keyboard has not only proven extremely adept at enabling digital phenotyping of its users’ affective and cognitive states, but is also sensitive enough to their unique typing patterns that it can serve as an effective behavior-based biometric user identification and authentication tool. Sun et al. (2017) created DeepService, a multi-view multi-class deep learning method which is able to use data collected by the BiAffect keyboard to identify users with an accuracy rate of over 93% without using any cookies or account information. Until recently, the use of keystroke kinematics in hardware personal computer keyboards had been limited to similar continuous authentication applications, but physical keyboard sensing techniques are now expanding in scope to include identifying and measuring digital biomarkers as well (Samzelius 2016).

Mindful of the myriad potential concerns related to user privacy, data security and ethical implications inherent in the mass development and deployment of such applications, as well as in drawing conclusions based on findings generated using a relatively small number of smartphone users from a handful of geographic regions (Lovatt and Holmes 2017; Martinez-Martin and Kreitmair 2018), and remaining particularly cognizant of the clinical imperative to only use those methods informed by established transtheoretical frameworks—the overarching lack of which may have led to the current replication crisis in psychology and the medical sciences (Muthukrishna and Henrich 2019)—the research teams investigating BiAffect data streams have endeavored to adopt a deliberately paced approach that harmonizes the latest developments in cognitive science, psychological theory, nosology, and treatment with state-of-the-art deep learning techniques and statistical methods. By paying close attention to safeguarding the individual privacy and protected health information of its users, and by adopting the most transparent possible model of sharing research techniques and findings in order to prioritize the use of digital phenotyping data for ethical medical applications, the BiAffect platform has been built on the twin paradigms of open source and open science as an invitation to collaborators from around the world to replicate, validate, amend or correct our hypotheses.

Perhaps one day we will all sport brain scanning ski caps that tell us how we feel, and install BCI implants to communicate wordlessly with our gadgets and with one another, while our IoT devices infer our emotions by analyzing our behavior at a distance; in the meantime, there is already no dearth of data streams readily available for passively mining users' mood, cognition, and much more with greater preservation of privacy and potential for predictiveness.

Acknowledgements We are grateful to the Robert Wood Johnson Foundation, the Prechter Bipolar Research Fund, Apple, Luminary Labs, and Sage Bionetworks, all of whom have helped enable much of the research discussed in this chapter. Jonathan P. Stange was supported by grant K23MH112769 from NIMH.

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Chapter 14
Studying Psychopathology in Relation to Smartphone Use: From Self-reports to Objectively Measured Smartphone Use Behavior

Dmitri Rozgonjuk, Jon D. Elhai, and Brian J. Hall

Abstract Smartphones allow for several daily life enhancements and productivity improvements. Yet, over the last decade the concern regarding daily life adversities in relation to excessive smartphone use have been raised. This type of behavior has been regarded as "problematic smartphone use" (PSU) to describe the effects resembling a behavioral addiction. In addition to other problems in daily life, research has consistently shown that PSU is linked to various psychopathology constructs. The aim of this chapter is to provide an overview of some findings in PSU research regarding associations with psychopathology. We also discuss some of the theoretical explanations that may be helpful in conceptualizing PSU. We then take a look at self-reported PSU in relation to objectively measured smartphone use, and, finally, provide some insight into current findings and future opportunities in objectively measuring smartphone use in association with psychopathology measures. This chapter may be useful as an introductory overview into the field of PSU research.

Keywords Problematic smartphone use · Smartphone addiction · Smartphone use disorder Internet addiction · Technological addictions · Psychopathology · I-PACE

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Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_14

14.1 Introduction

Smartphones provide many advantages to society that were unthinkable before the mid-to-late 2000s. In addition to the traditional voice calls and text messages, smartphones are essentially small computers that provide access to the Internet and various applications with utility ranging from productivity enhancement to entertainment. These features have the capability to facilitate important daily activities. Furthermore, with a smartphone, one may purchase their meals, clothing, or other necessary items without actually stepping into a physical store. These activities can be conducted almost anywhere, anytime.

In fact, because smartphones allow for efficient connectivity and even the replacement of many in-person, face-to-face daily-life activities, people may increasingly opt for using smartphones to execute their tasks. This preference may be associated with more frequent smartphone use as a result. Excessive engagement with smartphones, however, can be associated with several detrimental daily life conditions.

In this section, we (a) introduce the concept of problematic smartphone use, (b) describe how smartphone use may be related to psychopathology, (c) review how studies have implemented objectively measured smartphone use coupled with psychopathology constructs, and (d) explore how smartphone features could be used in psychopathology research. A plethora of research has been conducted in this domain since the previous edition of the current chapter (Rozgonjuk et al. 2019a). In this updated work, we will also discuss additional novel and interesting findings in the field.

14.2 Problematic Smartphone Use and Smartphone Addiction

Soon after the initial emergence of smartphones, concern about people spending excessive time on their devices was raised. In fact, such concern was already noted during the pre-smartphone era with internet use (Young 1996; Young and Rogers 1998), and with earlier mobile phones (Bianchi and Phillips 2005). However, smartphone ownership quickly became prevalent in modern society. The extreme portability and easy accessibility may have led some people to engage in excessive smartphone use.

Smartphone “addiction” is not recognized as a *bona fide* disorder. Nonetheless, it is an important construct that is studied in the scientific literature. Some research has used the term “smartphone addiction” (Kwon et al. 2013b) or “proneness to smartphone addiction” (Rozgonjuk et al. 2016). More recently, researchers have tended to avoid labeling this construct as an “addiction”. One of the most popular conceptualizations has been labeled as “problematic smartphone use” (PSU) to emphasize the adversity related to excessive smartphone use, and to avoid addiction terminology (Panova and Carbonell 2018).

PSU could be described by some emotional, cognitive, and behavioral difficulties associated with (excessive) smartphone use. Frequently, the framework inspired by addiction research has been implemented, suggesting that PSU could be characterized by symptoms such as withdrawal (negative affect when separated from one's smartphone), tolerance (increased need to use smartphones), and daily-life disturbances (impairment at work/school and/or health problems), among others (Kwon et al. 2013b). However, it should be noted that by using "problematic smartphone use" as the term describing similar conditions (e.g., smartphone "addiction"), there is still no consensus regarding using this term. One possible reason is that "problematic" could either describe a person being on the way from "healthy" to experiencing full blown psychopathology symptoms, or it could be the end condition in itself. Therefore, another proposed term is "smartphone use disorder" (Lachmann et al. 2018; Montag et al. 2019; Sha et al. 2019). With that being said, we will continue using the "problematic smartphone use" terminology in this text, while acknowledging that debate regarding terminology is ongoing.

How exactly is this *problematic* condition assessed? Typically, self-report measures (questionnaires) have been used. For example, inventories such as the Smartphone Addiction Scale (SAS), developed by Kwon et al. (2013a, b), include symptom-based items adapted from substance use disorder scales and criteria, which assesses functional impairments associated with PSU. The SAS, and its shorter version SAS-SV (Kwon et al. 2013a), are probably the most commonly used contemporary instruments for measuring PSU, and have demonstrated adequate psychometric properties (Demirci et al. 2014).

Mental health problems related to (self-reported) PSU have been found across different cultures, ranging from the Americas (Elhai et al. 2018b; Khoury et al. 2017), Europe (Laconi et al. 2018; Lopez-Fernandez 2017), and Asia (Elhai et al. 2020d; Kwon et al. 2013a); see also a meta-analysis by Olson et al. 2022. Apparently, concerns regarding PSU have been raised almost all over the world, further emphasizing the need for understanding this phenomenon. We now focus more specifically on mental health-related correlates of PSU.

14.3 How May Psychopathology Relate to Increased Smartphone Use?

To answer how and why psychopathology may be linked to increased smartphone use, we will briefly introduce some theoretical conceptualizations used in the domain of digital technology use and media engagement. Specifically, we first discuss Uses and Gratifications Theory (UGT; Blumler 1979), followed by the Compensatory Internet Use Theory (CIUT; Kardefelt-Winther 2014), and the Interaction of Person-Affect-Cognition-Execution model (I-PACE; Brand et al. 2016, 2019).

UGT posits that people actively seek out specific media to satisfy their psychological needs (Blumler 1979). These particular needs are the main drivers of certain types of media selection (Rubin 2009). There are several gratifications, or need satisfactions, that people obtain from their mobile phones, such as social need fulfillment, seeking information online, and relaxation (see Sundar and Limperos 2013 for a review of media gratifications). Broadly, gratifications have been divided into three typologies (Stafford et al. 2004): content (obtained from media content, e.g., reading news), process (from using the media, e.g., surfing the web), and social (media as a social environment, e.g., communicating with others). Derived from these gratifications, different media may have respective uses. In a study by van Deursen et al. (2015), smartphone use has broadly been categorized into process and social use, and shown that PSU was related to process, but not social smartphone use. On the other hand, there are also studies that show the prevalent role of social media use in developing PSU (Lopez-Fernandez 2017; Rozgonjuk et al. 2018c, 2020b; Sha et al. 2019). In some other studies, adverse factors in daily life (e.g., poor emotion regulation, intolerance of uncertainty, etc.) have been linked to non-social smartphone use (Elhai et al. 2017b, c; Rozgonjuk et al. 2019c; Rozgonjuk and Elhai 2019).

Another relevant tenet of UGT is that there are individual differences in engagement with media (Blumler 1979). In other words, levels of motivation to satisfy one's needs, but also differences in personality traits may drive some people to engage in higher levels of smartphone use. Regarding personality traits, lower willpower may reflect the core vulnerability towards developing addictive tendencies with digital technologies (Lachmann et al. 2019). Social media engagement was positively associated with extraversion and negatively correlated with conscientiousness (Montag et al. 2015). The role of higher neuroticism in greater PSU has also been demonstrated (Marengo et al. 2020). In addition, biological factors, such as age and sex of a smartphone user, may drive differences in engagement; it has been found that younger age predicts more smartphone use, while findings with gender are mixed (Mitchell and Hussain 2018; Horwood et al. 2021).

An additional potential driving factor of these individual differences may manifest in how people cope with experiencing negative affect. Here, CIUT (Kardefelt-Winther 2014) is useful to conceptualize why some people have higher levels of smartphone use. According to CIUT, people may engage in excessive technology use in order to alleviate negative affect. Some people who experience stressful life events cope with their negative emotions by using their smartphones (Kardefelt-Winther 2014). In fact, the SAS (Kwon et al. 2013b) includes items such as "Being able to get rid of stress with a smartphone" and "Feeling calm and cozy while using a smartphone", suggesting that emotion regulation may be a central motive for excessive smartphone use. CIUT has been used to conceptualize psychopathology in relation to PSU (Elhai et al. 2018c; Rozgonjuk et al. 2019c; Rozgonjuk and Elhai 2019; Zhitomirsky-Geffet and Blau 2016).

A more comprehensive approach explaining the associations between digital technology engagement and other psychological and environmental variables is the Interaction of Person-Affect-Cognition-Execution (I-PACE) model of specific Internet-use disorders (Brand et al. 2016, 2019). Based on the cognitive-behavioral model of pathological Internet use by Davis (2001), the I-PACE takes the process approach regarding the development of problematic digital technology use. According to the

I-PACE model, individual differences in predisposing variables, such as personality traits, genetics, and psychopathology, drive the affective and cognitive responses to stimuli. These responses interact with the individual's coping and decision-making that results in the use of certain Internet-based media and platforms. In some cases, this may result in problematic digital technology use, such as PSU. Several studies have used the I-PACE model as a theoretical framework in explaining the associations between daily-life adversities and PSU (Carvalho et al. 2018; Duke and Montag 2017; Rozgonjuk et al. 2020e).

Research findings have consistently demonstrated that PSU severity is associated with mental disorder symptom severity (mainly mood-related disorders). PSU is positively correlated to increased severity of depression and anxiety (reviewed in Elhai et al. 2017a), including social anxiety (Elhai et al. 2018d; Enez Darcin et al. 2016), and PTSD symptoms (Contractor et al. 2017). In addition, PSU has been associated with transdiagnostic symptoms. These are psychopathology-related characteristics that tend to overlap between different mental disorders (e.g., mood and anxiety disorders) and are considered to be core vulnerability factors in mental disorders (Krueger and Eaton 2015). Studies have found that PSU is associated with impulsivity (Contractor et al. 2017; Peterka-Bonetta et al. 2019), boredom proneness (Wolniewicz et al. 2019), procrastination (Rozgonjuk et al. 2018a), anger and worry (Elhai et al. 2019), excessive reassurance seeking (Elhai et al. 2020a), and lower distress tolerance and mindfulness (Elhai et al. 2018b). Additionally, smartphone use has been shown to have detrimental effects on daily-life social situations (Dwyer et al. 2018; Kushlev et al. 2019). Finally, works on the associations between (excessive) digital technology use and different cognitive functioning domains (attention, memory, delay of gratification) show that more engagement is typically associated with poorer cognitive functioning (Wilmer et al. 2017). These findings could potentially explain the link between smartphone use and ADHD symptoms (Kushlev et al. 2016), as well as PSU's correlations with educational variables, such as surface approach to learning (Rozgonjuk et al. 2019b; Rozgonjuk et al. 2018c), and poorer academic outcomes (Kates et al. 2018).

One of the variables that has shown consistent associations with PSU severity (Elhai et al. 2020c) is fear of missing out (FoMO) on rewarding experiences of others (Przybylski et al. 2013). Unsurprisingly, FoMO has also been linked to negative affectivity (Elhai et al. 2018a; 2020b), trait neuroticism (Balta et al. 2018; Rozgonjuk et al. 2020c), depression symptoms (Yuan et al. 2021), as well as negative links to academic outcomes (Alt and Boniel-Nissim 2018; Rozgonjuk et al. 2019b) and daily-life productivity (Rozgonjuk et al. 2020c). Furthermore, while research has shown mixed findings in gender differences with regards to experiencing FoMO, FoMO has been associated with younger age (Elhai et al. 2020c; Rozgonjuk et al. 2020c). The reader might notice the apparent similarity between FoMO's and PSU's associations with other variables. Finally, recent work showed that FoMO may also lead to decreased emotional well-being, and that two dimensions of PSU—cyberspace-oriented relationships and physical symptoms—may drive this relationship (Gugushvili et al. 2020). FoMO may stimulate online relationships at the cost of offline relationships, and physical problems (e.g., pain in neck and wrists) due to excessive smartphone use could contribute to poorer psychological well-being, too.

To summarize, people differ in their motives for using various digital technologies, including smartphones. Yet, prevailing explanations indicate that seeking gratifications, and alleviating negative affect, are a central component of technology engagement. Findings in PSU studies have consistently demonstrated that one's affect regulation and ability to cope with stressful situations could be one of the most important factors driving problematic technology use and in turn increase mental burden as theorized by vicious cycle models (e.g., the I-PACE).

14.4 Objectively Measured Smartphone Use (OMSU)

A vast amount of research discussed above relies on cross-sectional study design which is one of the main limitations in the field. Additionally, most of these works used self-report inventories rather than measuring smartphone use objectively. Objective smartphone use retrieved by using specific tracking applications could overcome these limitations. People typically inaccurately estimate their smartphone use duration and frequency (Andrews et al. 2015; Boase and Ling 2013; Montag et al. 2015). Therefore, for the purpose of studying psychopathology's relations with digital technology engagement, using recorded behavioral measures may provide a more valid insight into smartphone use engagement (Andone et al. 2016; Miller 2012; Yarkoni 2012).

Probably the most straightforward approach to do that is to measure actual time spent using smartphones and the number of phone checks/screen unlocks. These measures should provide information on (a) how much time one spends on their smartphone (usage duration), and (b) how frequently one initiates interactions with their smartphone (usage initiation frequency). Phone-checking and time spent using smartphones (conceptualized as active screen time) could reflect different behavioral patterns (Rozgonjuk et al. 2018b; Wilcockson et al. 2018). Whereas the former may indicate more active engagement with a smartphone (e.g., checking for messages), the latter could reflect more passive content consumption (e.g., watching videos, browsing social media sites).

Based on the content of this chapter, one may have the following questions: (1) how is PSU related to OMSU, and (2) how are other psychopathological conditions associated with objectively measured smartphone use behavior? Results from studying relations between PSU and objective behavioral smartphone use data are mixed. For instance, while Lin et al. (2017) found that both smartphone use frequency and duration were associated with PSU severity, Rozgonjuk et al. (2018b) as well as Loid et al. (2020) found that only duration but not frequency was associated with PSU. Lin et al. (2015) showed that smartphone checking (but not screen time) was related to PSU severity. More recently, Elhai et al. (2021) found that the link between PSU and objectively measured screen time and phone-checking was very small and non-significant. These studies provide some support that phone-checking behavior and time spent on smartphones could be distinct behavioral measures, and that the behavioral manifestation of PSU could be screen time. However, it should also be noted that Wilcockson et al. (2018) did not find a relationship between the measures of PSU and OMSU. Recently, several additional studies have demonstrated the poor correlations between OMSU and self-reported smartphone use. For instance, Ellis et al. (2019) correlated several PSU measures to OMSU measures, and found that while some scales predicted OMSU (with typically low effect sizes), other scales did not. Therefore, some of the findings in this line of research could be attributed to using a specific self-reported (problematic) smartphone use instrument. A recent review and meta-analysis by Parry et al. (2020) showed that, based on more than a hundred reported effect sizes in the literature, self-reports of screen time do not align well with objectively measured screentime.

One of the aspects to consider in this context is also the distinction between the frequency and duration of *specific app usage* on one's smartphone. A study by Ahn et al. (2014) showed that different application categories and time of day may be indicative of problematic technology use. Specifically, differences in usage time and frequency of social networking services (SNS) were associated with PSU. One of the more used functions of smartphones is accessing social media and SNS; therefore, it may not be surprising that excessive social media use has been regarded as a vulnerability factor for developing PSU (Lopez-Fernandez 2017). Indeed, it has been recently demonstrated that PSU severity may differentially relate to use of different types of social media platforms. For instance, Rozgonjuk et al. (2020b) found that problematic WhatsApp and smartphone use are highly intertwined. In comparison to other platforms in that study (Instagram, Facebook), it could be argued that WhatsApp is more text-message-oriented and smartphone-based—and, hence, these problematic uses overlap. It has also been recently shown that distinct platforms may differ in their "addictive" potential (Rozgonjuk et al. 2020c) as well as their impact on everyday life (Rozgonjuk et al. 2020a). Montag et al. (2017) showed that objectively measured Facebook use duration on one's smartphone may be a more reliable measure in relation to other outcomes, such as the gray matter volume of nucleus accumbens (often regarded as the brain's reward center). On the other hand, Rozgonjuk et al. (2020) found that while PSU severity was associated with depression and anxiety symptom severity, as well as Instagram use frequency, Instagram use did not predict psychopathology severity.

In sum, there are discrepancies between self-reports and OMSU, but it seems that only retrieving and correlating OMSU variables to everyday life constructs may not clarify the picture in this line of research. As recent evidence shows, it may be more fruitful to investigate *what* people are doing on their device, instead of focusing on *how much* they are using their smartphone.

14.5 Objectively Measured Smartphone Use (OMSU) in Relation to Psychopathology

Thus far, we discussed some of the findings between both OMSU frequency and duration and PSU, but how are these OMSU data related to psychopathology variables? Probably the most studied relationship is between increased smartphone use and depression severity. Here, too, findings are mixed. For example, Saeb et al. (2015) found that both smartphone use duration and frequency are positively associated with depression severity. A study conducted among bipolar disorder patients found that while a depressive state was related to more screen time, a manic state was related to more frequent smartphone use (Faurholt-Jepsen et al. 2016). In addition, Elhai et al. (2018d) found that maladaptive emotion regulation was associated with higher baseline smartphone use duration. However, studies also found the opposite. Specifically, the aforementioned study by Elhai et al. (2018d) also demonstrated that lower depression severity predicted increased smartphone use duration over one week; and Rozgonjuk et al. (2018b) found that smartphone use duration was not predicted by depression, but lower depression severity was correlated to higher smartphone checking behavior. Elhai et al. (2021) found that while OMSU screen time was not correlated with psychopathology variables, a higher number of smartphone pick-ups was inversely associated with depression, anxiety, and stress. Finally, examining this issue at the specific social media platform level, Rozgonjuk et al. (2020) found that objectively measured Instagram use did not have a robust correlation with depression and anxiety symptom severity. It should be noted, however, that that study had a relatively small sample size with tracked Instagram use data which may pose restrictions to the interpretation of results due to low statistical power.

In general, literature suggests that OMSU is linked to severity of mood-related disorders. Even within those relationships, the number of studies is relatively small and there are mixed results, mainly due to methodological differences (see Ellis et al. 2019; but also Dogan et al. 2017, and Parry et al. 2020 for reviews on this matter). We mentioned some studies that investigated depression and bipolar disorder. However, the role of anxiety has also been investigated, with it not being a significant predictor of OMSU (Rozgonjuk et al. 2020). Research on other disorders in relation to OMSU is currently accumulating, but with a slow pace.

In conclusion, the number of studies where PSU, psychopathology and OMSU have been of interest, is small - but hopefully growing. A majority of those studies have investigated how mood-related disorders, such as depression, are related to smartphone use behavior. These studies suggest that the duration of smartphone use may be associated with higher intensity of depressive symptoms. Future research should investigate how OMSU is related to psychopathology other than mood-related disorders.

14.6 Using Smartphone Features to Measure Psychopathology

Beyond the relatively straightforward approach of using logged smartphone use duration and frequency, contextual data could provide additional insights into the relations between smartphone use and other variables. Over the last years, the feasibility of objectively observing smartphone use behavior improved significantly. One of the reasons is that it is now possible to retrieve and analyze various smartphone use logs stored on one's device. For instance, these objectively measured phone use data have been applied for personality research, predicting either phone use behavior from (self-reported) personality measures, or vice versa (Chittaranjan et al. 2011; Montag et al. 2014; Stachl et al. 2017; Stachl et al. 2020).

Another less-explored avenue in smartphone use and psychopathology research is using data from various sensors on one's device that could track the user's mobility and environmental conditions. These sensors could also be helpful in both measuring PSU and the relationship between smartphone use and psychopathology. Below we will outline some ideas that might be helpful in studying psychopathology by using one's smartphone sensors. In order to execute these ideas, one probably needs to use third-party applications that retrieve relevant sensor data and make data export feasible.

Contemporary smartphones typically include an **ambient light sensor** that measures light in the room (or outside); typically, the purpose of this sensor is to adjust the smartphone's screen brightness according to current lighting conditions. It could also be used to capture light levels of the environment in which the person is spending time. There is evidence that depression severity is related to the perception of ambient light, with higher depression levels predicting dimmer light perception (Friberg and Borrero 2000). However, those findings relied on self-reports, rather than objective measures. Ambient light sensor data from smartphones could provide further validation to these results. Additionally, it would be possible to test how frequently and for how long do people with depression spend time in dim environments while *using* their smartphone. This idea stems from findings where PSU and social media use are associated with poorer sleep quality (Amez et al. 2020; Woods and Scott 2016). Finally, light density could also inform us about people's sleep–wake cycles which are typically disturbed in depressive disorders (Dogan et al. 2017). This research might help in developing prevention and intervention approaches to the individuals in need.

Microphones in smartphones could help in studying the effects of noise on a person's well-being. Noise is related to poorer sleep quality and more annoyance (Basner et al. 2014); noise annoyance has also been linked to depression and anxiety (Beutel et al. 2016). Again, smartphones could assist research in that domain by recording the noise levels of a person's surroundings. This research could be helpful in studying the relationship between physical noise and psychopathology. Microphones could also be useful in stress recognition. For example, an application called StressSense (Lu et al. 2012) was developed for that function. This application is relatively intrusive, though, requiring recording audio and video conversations of the user. Another potential utilization of microphones could be in speech, language, and voice analysis (Cummings and Schuller 2019). For example, it is possible to infer a person's sentiment through word use (Rathner et al. 2018b). Similarly, psychopathological tendencies, such as depression, anxiety, and narcissism could be detected by the use of social words (Rathner et al. 2018a).

Weather could influence how people feel, with negative affect and/or fatigue being generally more experienced in colder and darker environments (Kööts et al. 2011). Contemporary smartphones may include a **thermometer** that tracks temperature of the surrounding environment, while a **barometer** provides data about atmospheric pressure, another factor shown to influence fatigue (Denissen et al. 2008) and migraine headaches (Kimoto et al. 2011). Again, the mentioned studies have either mainly relied on subjective self-report data and/or more aggregate meteorological data from a local or national meteorological centre. Thermometers and barometers embedded into one's smartphone may provide more accurate temporal data on these environmental factors and their relations to mood changes and potential psychopathology.

Levels of physical activity and mobility could be measured with a smartphone's **accelerometer**. This sensor can be found in fitness trackers as well as in smartphones. Accelerometers provide data that could inform about one's number of steps walked/run, flights of stairs climbed, and distance traveled on foot during a given day. Smartphone apps based on this sensor tend to be quite accurate in providing information about the user's step count (Case et al. 2015). Little or no physical activity is generally associated with poorer mental health (Hiles et al. 2017) as well as increased smartphone use (Lepp and Barkley 2019). Using the data from accelerometers could help in that line of research. In addition, investigating a smartphone user's gait patterns (gait acceleration and walking speed) over a period of time might also be indicative of a person's affective state and potential psychopathology. Some support for these relationships are provided in the scientific literature where more sadness and depression were associated with reduced walking speed (Michalak et al. 2009). Additionally, different wearables (e.g., a smartwatch) could complement smartphone data by providing additional measures such as heart rate. This more direct index of physical activity could help in discriminating between a regular walk and a physical exercise session, further specifying the smartphone user's physical activity patterns.

Another feature that provides insight into one's mobility is the **global positioning system (GPS)**. GPS utilizes satellite technology in order to calculate and pinpoint one's location. This technology also allows for investigating the smartphone user's mobility patterns on foot or by vehicle. While GPS might provide more accurate data of one's mobility, another (but less accurate) method to track one's mobility is to investigate **movement between cell towers**. Moving between cell towers basically means that a person (and their smartphone) will be changing their geographical location between the reception areas of different cell phone signalling towers. For instance, in a study by Faurholt-Jepsen et al. (2016) with bipolar disorder patients, depressive states were related to less movement between cell towers, while more severe manic symptoms predicted more movement between cell towers. In other words, while depressive symptoms may be related to less mobility, psychological states including higher arousal could be manifested in more mobility. The idea that people who are in a depressive phase are expected to travel and stay outside less often is also demonstrated in a study by Gruenerbl et al. (2014). Location data provide additional insights into a person's whereabouts and the time spent at a specific location, which could be associated with other addictive behavior comorbidities, like alcohol use in relation to proximity or duration in a bar.

The combination of the aforementioned utilities could provide a more accurate and valid representation of one's mental health condition. Elaborate machine learning algorithms that include smartphone usage frequency and duration, different sensors' data, and external factors (e.g., socio-demographic data, date and time of day of smartphone usage, additional self-reported measures, etc.) have been developed to predict smartphone users' negative affective states (e.g., depression, anxiety; Hung et al. 2016; Ware et al. 2020) and stress (Reimer et al. 2017), social anxiety (Jacobson et al. 2020), and schizophrenia (Wang et al. 2017). Of note, machine learning methods are also finding their way into smartphone use research that is more dependent on self-reports (Elhai et al. 2020d; Elhai and Montag 2020).

In summary, in this section we described some of the opportunities of utilizing smartphone features and sensors to investigate affective states and potential psychopathology. While the list of sensors, and certainly the list of research questions, is not exhaustive, we find that there is an abundance of opportunities for conducting research that include objective behavioral data retrieved from smartphones. Including objective behavioral data could provide a ground for replicating and validating previous research findings in psychopathology studies that mostly rely on self-report and cross-sectional study designs.

14.7 Concluding Remarks

Smartphones have enhanced people's everyday lives by providing means for ubiquitous communication, information consumption, and productivity enhancement. However, excessive engagement in smartphone use has been associated with psychopathology. People who experience stress may try to cope with negative emotions by seeking gratifications provided by smartphone use. This hypothesis is, to some extent, supported by findings from several studies where PSU was associated with psychopathology symptoms and other core vulnerabilities driving those forms of psychopathology. In addition to measuring smartphone use duration and frequency, other features of smartphones could be helpful in studying psychopathology.

This line of research could also provide some academic and clinical implications. As mentioned in this text, there is a relatively small number of studies that objectively measured smartphone use and correlated these results to measures of psychopathology and PSU. Objectively measuring smartphone use may specify the relations between engagement in digital technology use and mental health. This type of measurement could also be useful in clinical settings, as knowing who, how, and why people engage in more digital technology use may help in intervention and prevention of mental illness.

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Chapter 15
Connecting Domains—Ecological Momentary Assessment in a Mobile Sensing Framework

Thomas Kubiak and Joshua M. Smyth

Abstract Ecological Momentary Assessment (EMA) is the state-of-the-art methodology to capture an individual's experiences (e.g., feelings, thoughts, behaviors) in daily life in an ecologically valid way. In this chapter, we outline the prominent role of EMA within a broader mobile sensing framework connecting domains of data acquisition from a range of sensing sources. We particularly highlight the advantages of context-aware assessment strategies that link the assessment of experiences to specific sensing events or patterns. Finally, we discuss strategies that go beyond assessment to implement innovative Ecological Momentary Interventions in real-life.

15.1 Ecological Momentary Assessment

Ecological Momentary Assessment (EMA) is a state-of-the-art assessment approach that aims at capturing momentary self-reports in naturalistic settings employing "electronic diary" style methodologies. In this chapter, we will briefly highlight the role of EMA as a method for investigating core research questions in behavioral science in the context of mobile sensing. EMA is an essential tool that can be used for linking mobile sensing data, behavioral and physiological data, and environmental data, to an individual's real-life experience that lies at the core of most research questions in the behavioral science. Starting with a brief characterization of EMA among other real-life methodologies and its key features of (quasi) real-time, real-life, and high frequency measurements, we will provide examples of research demonstrating how EMA may be linked to other sources of mobile sensing data in fruitful ways. Finally, we will discuss how the use of EMA may be extended to interventions in a broader mobile sensing framework.

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_15

15.2 Capturing Experiences in Real-Life

EMA (and related approaches, such as Experience Sampling) is generally construed as comprising a range of self-report approaches that aim to repeatedly capturing momentary experiences in everyday life, providing an opportunity to model intra-individual dynamic processes (Smyth et al. 2017; Stone et al. 2007). Although EMA has traditionally focused on self-reports of internal states, behavior, and context (Kubiak and Stone 2012), as will be discussed below, there is growing application of EMA methods supplemented by other data streams (e.g., wearable sensors, performance tasks). Currently, EMA is typically implemented on smartphones or other devices that are readily carried or worn in everyday life (Kubiak and Stone 2012; Kubiak and Krog 2012). In a typical EMA design, individuals are prompted (e.g., their device makes a sound or vibrates), usually several times throughout the day, to complete self-reports on their momentary experiences; these reports are delivered via short surveys, diary entries, text messages, and other modes.

EMA is a core method within the broader research framework of Ambulatory Assessment (Kubiak and Stone 2012). Ambulatory Assessment is an 'umbrella' concept comprising methodologies that share the common aim of capturing phenomena in situ (Fahrenberg 1996; Fahrenberg et al. 2007). In addition to the self-report data typically captured by EMA, these 'real-life' methodologies also include—but are certainly not limited to—wearable or other sensors that allow for the ambulatory monitoring of physiological signals, actigraphy (e.g., to measure activity and movement), and GPS-based location tracking. Many performance tasks for smartphones, such as ambulatory cognitive testing (e.g., Sliwinski et al. 2018), are also being developed and integrated into these methodologies as well (For additional information on Ambulatory Assessment approaches, see Trull and Ebner-Priemer 2009; Mehl and Conner 2012).

EMA shares key features with other strategies of Ambulatory Assessment with its (near) real-time assessment and its focus on real-life settings outside the laboratory (Trull and Ebner-Priemer 2009), and typically generates rich within-individual data with frequent repeated measurements (often referred to as intensive longitudinal data; e.g., Shiffman et al. 2008; Bolger and Laurenceau 2013). Given this in situ collection style relying on momentary (not lengthy retrospective) recall, EMA data exhibit enhanced ecological validity, minimize recall and reporting biases, and allow for the detection of fine-grained dynamic changes in behavioral process over time in real-life contexts (Shiffman et al. 2008).

15.3 EMA at the Center of a Mobile Sensing Framework

Although EMA can be used to assess self-reported behaviors (such as eating behavior or interpersonal interactions), a unique strength and opportunity for EMA lies in connecting to the *experiential domain* (Conner and Feldman Barrett 2012): EMA allows for capturing an individual's feelings and thoughts in a given moment, such as the assessment of emotions and affect, appraisals of situations, thoughts/cognitions, intentions, and emotion regulation strategies an individual employs (among many other possibilities). Importantly, there are few, if any, other methods for capturing intrapsychic thoughts and feelings *reliably and with specificity*; thus, in any research context or question where these are valuable (or requisite) sources of information, self-report is essential—and EMA provides one valuable method to capture this data. In doing so, we posit that EMA may be considered to be at the core of a mobile sensing framework (see Fig. 15.1): EMA may serve as a central, integrative hub linking mobile sensing data from different sources to the experiential component (in real-life and real-time) and, thus, be important for a range of applications in behavioral science including domains addressed in this volume (e.g., persuasive health technologies, digital markers of cognitive function). Given the rapid technological progress in the field of mobile sensing, one can expect the data sources mentioned in our framework to expand considerably in the future. For example, there are promising developments for the monitoring of biomarkers under real-life conditions, and emerging approaches for speech analysis that may serve as additional data sources for affect and emotions (Mehl et al. 2012).

An example from our own research is the integrative assessment framework developed within the European Determinants of Diet and Physical Activity (DEDIPAC) knowledge hub (Lakerveld et al. 2014). The aim of the DEDIPAC integrative assessment framework is to capture eating behavior, physical activity, and sedentary behaviors concurrently with individual, interpersonal, and environmental correlates and

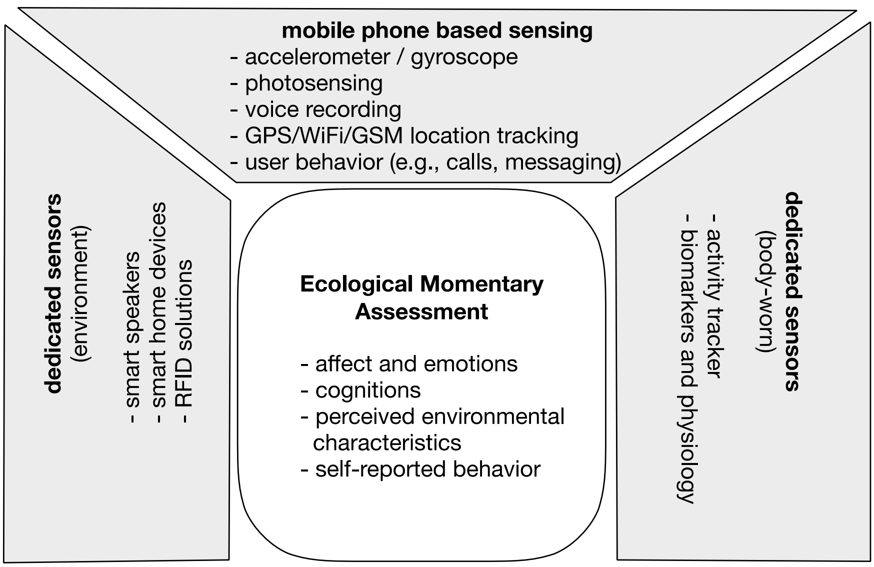

Fig. 15.1 Ecological momentary assessment within a mobile sensing framework

determinants within a single assessment tool. In this framework, self-reports on affect and self-regulatory strategies are assessed via smartphone and complemented with data sources from activity monitoring (accelerometry), location tracking based on the Global Positioning System (GPS), and mapping to Geographical Information Systems (GIS; van Laerhoven et al. 2017). In addition, a bar code scanning feature is implemented to capture a range of food products bought or consumed. Initial piloting focused on the consumption of sugar-sweetened beverages and yielded promising data for this system to serve as an integrated data capture tool (Van Laerhoven et al. 2017; Wenzel et al. 2019); many similar approaches exist and such integrative strategies hold great promise for research and practice.

15.4 Sampling Approaches, Including Context-Aware Sampling

EMA typically builds on signal-contingent sampling, event-contingent sampling, interval-contingent (or time-based) sampling, or a combination of these. In *signal-contingent sampling* individuals are signaled ('beeped') by the smartphone to complete a set of standardized questions on their momentary experience (or experiences since the prior signal), usually several times a day in random intervals spaced across the waking hours. Signal-contingent sampling plans are particularly well suited to capture snapshots of experiences and psychological processes that occur throughout the day (e.g., affect), and are most likely to capture "representative" (i.e., typical) moments for an individual. In *event-contingent sampling*, data entry is triggered by the individuals themselves in response to some eliciting stimulus (either internal or external, as specified by the researcher). Event-contingent sampling is best used to capture well-defined, circumscribed episodes that a research participant can identify and respond to. Event-contingent triggers might include participants pressing a button to activate an EMA survey shortly after an event of interest occurs (e.g., drinking a sweetened beverage), or if an earlier EMA survey confirmed the presence of such an event (Shiffman 2014). *Interval-contingent* sampling are based on specific times, such as on the hour each hour, and might be used to characterize temporal processes or to study the impact of temporally entrained stimuli.

Integrating EMA within a broader mobile sensing framework opens up new avenues of sampling an individual's experiences: In *context-aware sampling* (Intille et al. 2003; Intille 2012), any predefined data pattern acquired through any of the sources within the mobile sensing framework may trigger a signal for EMA data entry. For example, an increase in heart rate captured via dedicated sensors may prompt the individual to complete a self-report on his or her perceived stress. Episodes of physical activity assessed via an actigraph device may trigger self-report on a person's feelings afterwards. Using a similar approach, Ebner-Priemer and colleagues (2013) were able to capture bouts of physical activity and concomitant affect that may have easily gone unnoticed if a signal-contingent sampling scheme had been used (that would have relied on sampling probability to capture, or co-occur, with sufficient physical activity bouts to be statistically modeled).

15.5 Ecological Momentary Interventions

The EMA approach is increasingly being extended beyond a mere assessment tool by implementing interventions to be delivered in situ, often via software on the smartphone itself. This approach of Ecological Momentary Intervention (EMI, Heron and Smyth 2010) offers novel opportunities for delivering individually tailored interventions when they are most effective and needed, one example being the just-in-time intervention approach (Smyth and Heron 2016). EMI has been found to be an effective approach for a range of applications, including mindfulness training (Rowland et al. 2016, 2018), smoking cessation (Hébert et al. 2018), and stress-management (Smyth and Heron 2016).

If integrated in a mobile sensing framework, context-aware strategies may substantially enhance interventions: A compelling example in this regard is the study by Gustafson and colleagues (2014) examining the impact of implementing ‘warning messages’ (based on location tracking) whenever individuals out of alcohol rehabilitation approached a high-risk location like a bar or a liquor vending shop. They demonstrated that the provision of these messages was associated with much improved treatment outcome (e.g., risky drinking days). In a similar vein, comprehensive mobile sensing approaches that integrate an EMA/EMI component have been developed within the European Innovation Partnership on Active and Healthy Ageing (EIP on AHA) that aims to enable older individuals to live independently despite functional and/or cognitive impairments. One example from this work is the development and implementation of systems that produces a mobile sensing based estimation of the risk of falls (one of the most important risks for this sample); this information is able to be collected, processed, visualized and then fed back to at-risk frail older adults and their health care professionals as a means of fall prevention (e.g., De Backere et al. 2017).

15.6 Summary and Conclusions

For many applications in the behavioral and health sciences, EMA can serve as a core component within a mobile sensing framework. Its unique contribution lies in connecting different data sources (across types of data and various sampling densities) to an individual’s experiences (the assessment of which can be curated by researchers to topics of interest and relevance). Implementing context-aware strategies and providing individuals interventions during at-risk moments or in risk-elevating contexts based on real-time EMA and/or sensor data opens up tremendously promising avenues for research and care. Given these systems, multi-modal information (from EMA, sensors, and other data sources) can be collected, processed, and used to trigger intervention efforts or provided to patients, caregivers, and/or providers. Well-developed mobile sensing platforms coupled with empirically informed data analysis/processing approaches (i.e., to extract the meaningful information and suggest clinical or other action) have tremendous potential for enhancing the reach, efficiency, and sophistication of monitoring, prevention, and intervention efforts at the individual and public health levels.

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Chapter 16
Momentary Assessment of Tinnitus—How Smart Mobile Applications Advance Our Understanding of Tinnitus

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Abstract Tinnitus is a condition associated with a continuous noise in the ears or head and can arise from many different medical disorders. The perception of tinnitus can vary within and between days. In the recent years, Ecological Momentary Assessments of tinnitus have been used to investigate these tinnitus variations during the daily life of the patients. In the last five years, several independent studies have used Ecological Momentary Assessment to assess tinnitus. With this chapter, we want to review the current state of this research. All the EMA studies revealed a considerable variability of tinnitus loudness and tinnitus distress. It has been found that emotional states and emotional dynamics, the subjectively perceived stress level and the time of the day exert influence on the tinnitus variability. In summary, the EMA method revealed a good potential to improve our scientific understanding of

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https://doi.org/10.1007/978-3-030-98546-2_16

tinnitus. Furthermore, it also showed that it can be used to understand the individual differences of tinnitus—and may even be used as a tool for individualized diagnostic and treatment. We will also give three examples where EMA sampling was used to describe and evaluate tinnitus treatment. In summary, we suggest that EMA studies can lead to improvements of existing research methods in the field of tinnitus.

Tinnitus is a condition associated with a continuous noise in the ears or head and can arise from many different medical disorders. The condition is very common and affects approximately 10–15% of the adult population in the western societies (Nondahl et al. 2012). Severe cases of tinnitus can be accompanied by anxiety, depression, insomnia, and concentration problems all of which can impair quality of life (Kreuzer et al. 2013). Although much progress has been made, tinnitus remains a scientific and clinical enigma. There is little evidence for effective tinnitus treatments with cognitive behavioral therapy being the best evidence-based treatment option so far (Cima et al. 2014) and no licensed pharmacological therapy. The research on tinnitus and the development of effective treatments is challenging for two reasons: First, there is a large patient heterogeneity among the tinnitus sufferers (Elgoyhen et al. 2015). At least 13 different causes of tinnitus have been identified (Baguley et al. 2013) and the clinical phenotype is largely variable on various dimensions such as aetiology, perceptual characteristics of the sound (i.e. pitch and loudness), time since onset, levels of conscious awareness and perceived distress. All of them potentially influence the individual treatment response of the patient. Second, the majority of patients report that their conscious perception of tinnitus varies within and between days. There are moments with loud and prominent tinnitus perception, but also moments with reduced tinnitus loudness. The reasons for these fluctuations are largely unknown. This not only introduces a methodological challenge for the assessment of tinnitus in basic and clinical research. It also leads to the question about the underlying neurobiological mechanisms of this moment-to-moment fluctuation. A better understanding of these mechanisms might reveal innovative ways for clinical interventions. The systematic assessment of these tinnitus fluctuations, however, would require the measurement of tinnitus with a high sampling rate, ideally during the everyday life of the patient and with a minimum of disturbance to the routine activities. The classical paper-and-pencil questionnaires that are typically used in tinnitus research are hardly suitable for this type of research. In the year 2013, we developed the TrackYourTinnitus App (Schlee et al. 2016) that allows to measure the individual tinnitus fluctuations using the research methodology called Ecological Momentary Assessment (EMA, Stone and Shiffman 1994). In this chapter we provide a review of almost five years of EMA research on tinnitus and summarize the results of this line of research.

16.1 Ecological Momentary Assessment in Tinnitus

Ecological Momentary Assessment (EMA) is a new research method allowing to systematically collect self-reports of cognition, behavior and emotions in the daily lives of the participants (Kubiak and Smyth 2019). The method is also known by the names "Experience Sampling" (Czsikszentmihalyi and Larson 1987) or ambulatory assessments, but in the recent years the term "Ecological Momentary Assessment" is more often used. The idea of this method is based on the desire to measure human behavior, cognition and perception in real-world settings rather than laboratory or clinical settings. Retroactive recall of perceptions, cognitions, emotions—and also behavior—can be biased by memory decay and mental reconstruction (see e.g. Fredrickson 2000). Therefore, the EMA methodology favors a prospective measurement to assess the self-report data in the current state. A technical signaling device is used to prompt the participant with a short questionnaire asking questions on the current situation. In the context of tinnitus, EMA is used to collect self-reports about the current perception of the tinnitus and other factors that are closely related to tinnitus such as stress or emotional arousal. While earlier studies on EMA relied on different technical handheld devices, nowadays almost all EMA studies utilize smartphone devices which are owned by a large percentage of the society. In the recent years, the number of studies using smartphone-based or internet-based technologies have largely increased (Kalle et al. 2018). Among them, two studies have also investigated the effects of the long-term use of EMA on the tinnitus distress of the patients: Henry and colleagues reported that the tinnitus distress of 24 study participants did not change significantly during an EMA study with a duration of two weeks (Henry et al. 2012). These effects were again tested on two different groups of participants of the TrackYourTinnitus app (Schlee et al. 2016), using the app for more than one month ($n = 66$) or less than a month ($n = 134$). In both groups, there was no significant change in the tinnitus loudness nor tinnitus distress over time. This is an important prerequisite for future EMA studies in the field of tinnitus. First, these results show that the method of repeated question about the tinnitus is not increasing the perceived tinnitus loudness/distress of the study participants. Second, the results suggest that the repeated measurement of tinnitus is not introducing a systematic bias towards an increase or decrease of tinnitus loudness/distress. The methods seems to be appreciated by the patients: in a study by Goldberg and colleagues, 80% of the participants in an EMA study on tinnitus felt that this is a good way to measure tinnitus (Goldberg et al. 2017).

16.2 Tinnitus Fluctuates Within and Between days

In the recent years, three different studies on tinnitus fluctuations using the ecological assessment method have been published. They all demonstrated relatively large fluctuations of the individual tinnitus perception.

Henry and colleagues reported 2012 a two-weeks study using a Palm Pilot device (Henry et al. 2012). The palm device created four alerts per day and prompted the 24 participants to answer a short version of the Tinnitus Handicap Inventory (THI-S). The authors described a strong variability measured with the THI-S in different time blocks and locations. The highest mean THI-S score with 19.3 was reported for the time period 8 am–11 am when the participants were travelling, while the lowest mean THI-S score of 13.2 was reported in the evening from 5 pm–8 pm when the participants recorded that they are "somewhere else". Mixed model analysis showed a significant main effect for the location, but not for the time block.

In another study, Wilson and colleagues reported an EMA study on 20 participants during a period of two weeks (Wilson et al. 2015). At four random time points per day, the tinnitus participants received a text message with a hyperlink to an online survey of six questions. The response of the participants to the main question "In the last 5 min, how bothered have you been by your tinnitus?" varied substantially within the participant. A coefficient of variation (CV) was calculated for each participant and was reported in the range between 11.5% and 109.9%. The median CV was 48.8%, indicating a large variation of tinnitus perception over the two weeks study period.

In an analysis of the TrackYourTinnitus database (Probst et al. 2017a), Probst reported similar variability measures for the tinnitus loudness and the tinnitus distress. Tinnitus distress and loudness were both measured on a visual analog scale in the range between 0 and 1. In a sample of 306 users, the mean intra-individual variability of tinnitus distress was reported with 0.18, and the variability of the tinnitus loudness 0.17. In another analysis, Probst showed significant within-day variations of tinnitus with an increase of tinnitus loudness and distress during the night and early morning (Probst et al. 2017a).

In summary, all EMA approaches on tinnitus demonstrated large within- and between-day fluctuations of tinnitus. The amount of fluctuations varies between the individual participants. Examples of the tinnitus variability and the individual differences of it are given in all three EMA studies (Henry et al. 2012; Wilson et al. 2015; Schlee et al. 2016). These results demonstrate the feasibility of measuring the tinnitus fluctuation in the everyday life of the patients and open up a new line of research that allows to systematically investigate the influencing factors and the underlying neurobiological mechanisms. Studies on neurobiological mechanisms of these fluctuations are rare. In one study, it could be shown that the resting-state alpha activity in the auditory cortex of tinnitus sufferers fluctuates within minutes (Schlee et al. 2014). However, a relationship between these fluctuations of neuronal activity and the fluctuations of the tinnitus perception has not been shown yet. A better scientific understanding of the tinnitus variability is needed and can help to improve tinnitus treatment in the future. Some work on influencing factors for tinnitus fluctuations using EMA methodology will be discussed in the following chapter.

16.3 Which Factors Influence the Tinnitus Perception?

The TrackYourTinnitus project is an ongoing EMA study collecting data from tinnitus patients since 2013. The app is freely available in the app stores for iOS and Android devices in English, German and Dutch. The questionnaire of the app not only asks about the perception of tinnitus loudness and tinnitus distress. It also assesses information about the emotional arousal, and emotional valence using the self-assessment manikins (Bradley and Lang 1994), as well as the subjectively perceived stress level and concentration at the same time point. This data was used for several publications to further investigate the factors influencing the tinnitus perception.

Emotional states as mediators between tinnitus loudness and tinnitus distress. In an analysis on 658 users of the TrackYourTinnitus app, Probst et al. (2016a) discovered that emotional states partially explain the association between tinnitus loudness and tinnitus distress. Tinnitus loudness describes the individually perceived loudness of the tinnitus sound, while tinnitus distress describes the psychological annoyance that is associated with the tinnitus. In general, there is a linear correlation between tinnitus loudness and tinnitus distress. Hiller and Goebel reported a significant correlation of $r = 0.45$ between them (Hiller and Goebel 2007). Please note, a correlation estimate of $r = 0.45$ means that only 20.3% of the variance of tinnitus distress can be explained by tinnitus loudness. The remaining 79.7% of the variance need to be explained by other influencing factors. These other influencing factors are currently unknown. Possible factors are, among others, personality characteristics, the influence of comorbidities or emotional states.

Probst and colleagues hypothesized that the emotional states of the patient mediate the relationship between tinnitus loudness and tinnitus distress. The emotional states were characterized by two measures: emotional arousal and emotional valence. Emotional arousal can be understood as the physiological arousal associated with the emotional state. Higher values of emotional valence indicate positive emotional states, while smaller values represent negative emotions. In accordance with earlier studies, the results revealed a significant positive relationship between tinnitus loudness and distress. Additionally, it was found that emotional arousal and emotional valence are both significant mediators for the relationship between tinnitus loudness and tinnitus distress. An increase of tinnitus loudness also affects the emotional state leading to higher arousal and more negative emotions. This state of negative emotional arousal leads to increased tinnitus distress. Accordingly, more positive emotions are associated with lower tinnitus distress.

In Fig. 16.1 we show the path diagram summarizing these relationships and provide the numerical estimators of the model. Included in this figure is also the perceived stress level, which is an additional mediator reported by the same paper.

Stress as a mediator between tinnitus loudness and tinnitus distress. Furthermore, in the same publication, Probst reported that stress explains a significant proportion of the relationship between tinnitus loudness and distress (Probst et al. 2016b). There is a positive influence of the tinnitus loudness on the general stress level, indicating that a tinnitus loudness increases the general stress level (see the path

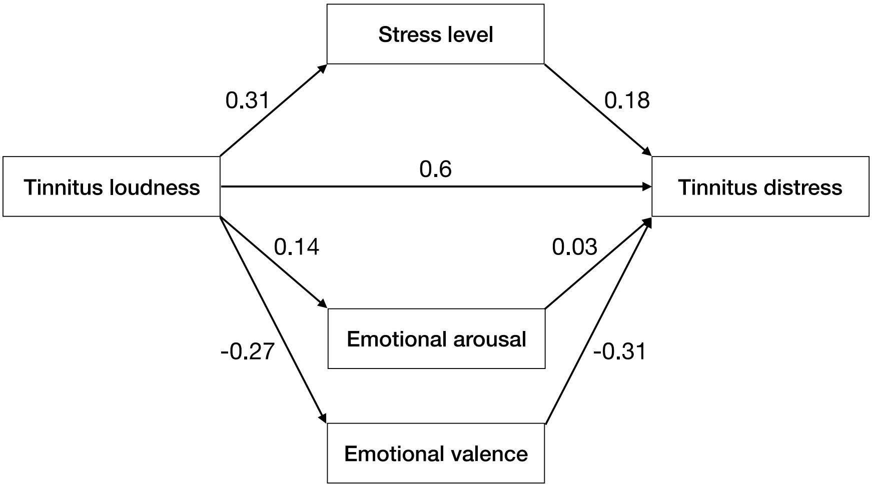

Fig. 16.1 Path diagram summarizing the multiple mediation model explaining the association between tinnitus loudness, tinnitus distress, stress level, emotional arousal and valence. Figure redrawn from Probst et al. (2016a)

diagram in Fig. 16.1, path estimate 0.31). The influence of the stress level was with 0.18 also positive, indicating that higher stress levels lead to higher tinnitus distress. Importantly, a statistical comparison of the mediator effects of stress and emotional valence revealed no significant difference. This indicates that both factors, stress and emotional valence, contribute similarly to the process between tinnitus loudness and tinnitus distress. Based on this data we would expect that clinical interventions reducing the stress level and enhancing positive emotions would lead to a reduction of tinnitus distress.

Emotional dynamics are associated with increases of tinnitus loudness, tinnitus distress and the relationship between them. According to Kuppens and colleagues, short-term dynamical changes of the emotional state within a person can be described by the following two measures (Kuppens 2015): Intra-individual variability of affect intensity (pulse) and intra-individual variability of affect quality (spin). Valence and arousal ratings were used for these measures of emotion dynamics. The intra-individual variability of the emotional intensity is called the “pulse”. It characterizes the variability of the emotional arousal over time. A person with high pulse is therefore characterized by quick changes between high and low emotional arousal. The pulse is calculated by the intra-individual variability of arousal measures in a longitudinal study. The intra-individual variability of the emotional quality is called “spin”. A person that can quickly change from sad to happy emotions would be characterized as a person with a high spin. The spin is calculated by the intra-individual variance of the valence measures in a longitudinal study.

Probst and colleagues analyzed the relationship between the emotional dynamics and tinnitus on 306 users of the TrackYourTinnitus application (Probst et al. 2016c).

They found significant positive correlations between tinnitus distress, measured with the Mini-Tinnitus Questionnaire (Mini-TQ), and the pulse ($r = 0.19$, $p = 0.001$). Also, the correlation between spin and tinnitus distress was significant ($r = 0.12$, $p = 0.035$). Patients with higher emotional dynamics are more often found with stronger tinnitus distress. Because the Mini-TQ was only used at the beginning of the study, the causal relationship between tinnitus and emotional dynamics could not clarified. In an additional analysis, multilevel modelling revealed that the relationship between tinnitus loudness and distress is stronger in patients with high emotional dynamics. In other words: patients with high emotional dynamics are more distressed if the tinnitus loudness increases, while patients with low emotional dynamics are less likely to show this reaction. Additionally, the authors report that high spin—but not pulse—is associated with increases of tinnitus loudness over time ($p < 0.01$). Based on these analyses, it can be hypothesized that clinical interventions improving emotional stability of the patients can be beneficial for patients with high emotional dynamics.

Tinnitus loudness and distress is higher during the night and early morning. In another analysis of the TrackYourTinnitus database, Probst and colleagues reported that the tinnitus perception depends on the time of day (Probst et al. 2017a). They analyzed the data of 350 tinnitus patients that have filled out enough assessments to allow a systematic analysis of within-day tinnitus variability. A total of 17,209 assessments were included. Using multilevel modeling with random effects, they analyzed the tinnitus perception in six different time periods: early morning (4 a.m. to 8 a.m.), late morning (8.a.m. to 12 p.m.), afternoon (12 p.m. to 4 p.m.), early evening (4 p.m. to 8 p.m.), late evening (8 p.m. to 12. a.m.), and night (12 a.m. to 4 a.m.). They found that the tinnitus loudness and distress are significantly higher during the night and early morning hours. Further research will be needed to understand the neurobiological mechanism underlying this circadian tinnitus rhythm.

In summary, EMA studies are able to measure systematic patterns of intra-individual tinnitus variability by repeated sampling of short questionnaires. The emotional states, the stress level, emotional dynamics and the time of the day have been identified as possible factors influencing the moment-to-moment variability of the tinnitus perception. However, the predictive value of these influencing factors—calculated over a large patient sample—is low, and differences between the individual patients are high. This leads to the idea that a long-term assessment of the tinnitus variability together with potential influencing factors can be used to identify for each individual tinnitus patient those factors with an impact on the subjective tinnitus perception. If the result of this analysis is fed back to the individual patient, she or he can potentially learn about situations that lead to an increase or decrease of tinnitus. With this knowledge about the own tinnitus, the patient would be in a position to control the tinnitus by changing the behavior. This concept was implemented in a mobile feedback service that was presented by Pryss and colleagues (2017). Future research will be needed to empirically test if this intervention leads to an improvement of tinnitus symptoms. If the claims hold true, this concept can be applied as an individualized treatment for chronic tinnitus patients.

16.4 Limitations of the EMA Studies in Tinnitus

There are several limitations of the EMA studies in tinnitus, which mainly affect the generalizability of the results. In 2017, Probst and colleagues compared the sample of the TrackYourTinnitus database with the users of the TinnitusTalk internet forum, and the patients representing at the University Clinic Regensburg (Probst et al. 2017b). The three patient groups differed significantly from each other with respect to age, gender and tinnitus duration. As shown in Fig. 16.2, the most prominent differences are: Participants between the age of 25 and 44 are overrepresented in the TrackYourTinnitus study, while older participants with an age over 65 years are less likely to use the TrackYourTinnitus app. The percentage of women using the modern technologies of the internet forum TinnitusTalk and the smartphone app TrackYourTinnitus is larger than in the sample of patients seeking help in the tinnitus center Regensburg. The percentage of tinnitus sufferers with acute tinnitus (duration less than three months) in the TrackYourTinnitus sample is higher compared to Tinnitus Center Regensburg. Patients with a tinnitus duration longer than 20 years less likely seek help in the tinnitus center, but rather use the TrackYourTinnitus app or the TinnitusTalk forum. These differences in the study samples need to be kept in mind when interpreting the results of EMA studies on tinnitus. Several interpretations of these differences are discussed in the paper (Probst et al. 2017b).

Another sampling bias may be introduced by the operating system that is addressed with the smartphone app. There are studies on the differences between the operating systems and how they influence the user's choice for the operating system and the cell phone; even minor personality differences have been found (Lim et al. 2014; Götz et al. 2017). With the TrackYourTinnitus app being available for iOS and Android, Pryss and colleagues investigated the differences between the iOS and Android users and found significant group differences in the age and tinnitus duration (Pryss et al. 2018): The Android users were on average 1.5 years older than iOS users (t(1443) $= -2.1, p = 0.035$). Also, the Android users also reported a longer tinnitus duration with a mean of 11.2 years, while the iOS users reported on average only 7.2 years

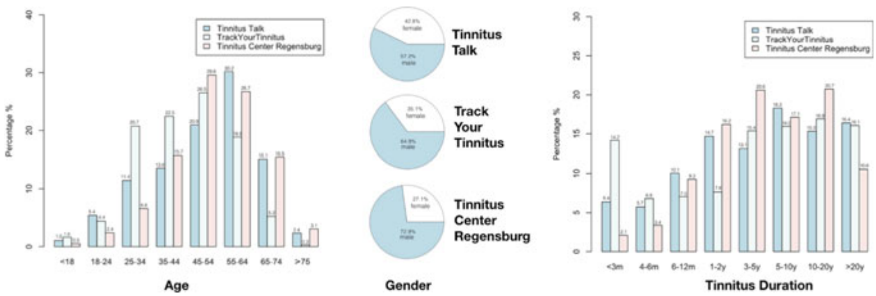

Fig. 16.2 Comparison between the samples of the EMA study TrackYourTinnitus, the online patient forum TinnitusTalk and the university-based tinnitus center Regensburg, published in Probst et al. (2017a, b)

($t(1214) = -6.72$, $p < 0.001$). No differences were found for gender, family history or causes of tinnitus. While the age differences between the user groups was only small, a remarkable group difference between the users of the different smart phone systems was found in tinnitus duration. Studies that are addressing only one operating system will need to take this difference into account when interpreting the results.

Furthermore, in 2015, Pryss and colleagues analyzed the number of users participating in the TrackYourTinnitus (Pryss et al. 2015a, b). At this time, 1718 users had downloaded the app, but only 822 have registered for the TrackYourTinnitus study. Among them, only 150 users had used the app more than ten times. These 150 users contributed to approx. 90% of the collected data. This analysis shows that the researchers lost a large percentage of participants in the process from downloading the app to the regular usage. This loss of users may introduce a bias to the sample and also reduces the efficacy of the study. Additional work will be needed to understand the reasons for this high attrition rate and find ways to avoid it. Promising research is already on the way with analyses concentrating on the incentive management of EMA studies in the medical domain (Agrawal et al. 2018). The goal of this research, also known as persuasive design research (Baumeister et al. 2019) is to identify features in eHealth smartphone apps that are enhancing the motivation of the users to participate for a long time. This knowledge can be important for both, smartphone apps delivering a clinical service to the patients as well as for smartphone apps in basic research.

16.5 Lessons Learned for Clinical Assessment of Tinnitus

With the ongoing TrackYourTinnitus study, several lessons for clinical assessment of tinnitus have been learned:

Assessment of tinnitus in clinical trials. The perception of tinnitus is characterized by within- and between-day variability that can bias the clinical assessment of tinnitus. So far, it has been shown that the emotional states and emotional dynamics, stress level, and the time of the day exert influence on the tinnitus perception. This is a danger for the reliability of the outcome measures in clinical trials. Since clinical trials often rely on a single measurement time point before and after the clinical intervention, the control of these measurement points is of importance. With the circadian fluctuation of the tinnitus (Probst et al. 2017a), the assessment should always be done at the same time of the day. Furthermore, since the tinnitus assessment can be influenced by the stress level and the emotions of the patients, efforts should be made to ensure comparable stress level and emotional states at all time points of tinnitus measurement. Additionally, based on the lessons learned from the EMA studies on tinnitus, we would suggest to collect tinnitus measurement at multiple time points before and after the clinical intervention.

Retrospective assessment of tinnitus. In the assessment of the clinical characteristics of tinnitus, some questionnaires include retrospective reporting of the tinnitus patients. Such a retrospective assessment can be biased by failure to recall the events correctly from memory. This recall bias was investigated in two studies using the TrackYourTinnitus app.

In one study, Pryss and colleagues (Pryss et al. 2018) concentrated on the variation of the tinnitus loudness. At the beginning of the study, participants were asked retrospectively if they have noticed variations in the tinnitus loudness in the past. Based on this answer, the participants were divided into a group experiencing the tinnitus loudness as varying and a group experiencing the tinnitus loudness as non-varying. Both groups used the TrackYourTinnitus app for at least 10 days to assess prospectively the variability of tinnitus loudness. The day-to-day variability of tinnitus loudness was calculated for all participants and compared across the two groups. There was no significant difference between the two groups ($t(258) = 0.19$, $p = 0.85$). The same test was repeated with patients using the app for more than 25 days; there was again no significant group difference ($t(126) = 0.96$, $p = 0.34$). If the patients would be able to recall the tinnitus loudness variability correctly from memory, we should have seen a significant difference between the groups. Both results were far from statistical significance. This demonstrates that the majority of the patients are not able to correctly recall the variability of their tinnitus loudness in the past.

In another analysis, the participants were asked retrospectively about the influence of stress on their tinnitus perception before starting the TrackYourTinnitus app (Pryss et al. 2018). The participants were able to rate if stress worsens their tinnitus, improves their tinnitus or has no influence. Using the prospectively assessed data on the tinnitus loudness, tinnitus distress and stress levels, multilevel models were calculated for all three groups. The results showed that higher stress levels are associated with higher tinnitus loudness and higher tinnitus distress ratings (all $p < 0.001$). Even in the participant group that reported retrospectively that stress improves their tinnitus, the analysis of prospective data indicated that increased stress leads to tinnitus worsening. In summary, both studies demonstrate a large discrepancy between the retrospective reporting of the tinnitus patients and the analysis of the prospective assessment of tinnitus.

16.6 Ecological Momentary Assessment and End-of-Day Diaries

While EMA is a promising tool in assessing chronic tinnitus experiences, it is not the sole option for curbing biases associated with memory decay and mental reconstruction. End-of-Day Diary (EDD) has been used for decades (e.g. Verbrugge 1980) in a variety of fields (e.g. eating behaviour; Debeuf et al. 2018; emotionality during the COVID-19 pandemic; Moroń and Biolik-Moroń 2021; chronic pain; Rost et al. 2016). Much like EMA, EDD reduces the time between experience and assessment by relying on the collection of data on a recurrent basis, usually daily. A direct comparison between EMA and EDD assessment in chronic tinnitus revealed minor differences between the methodologies (Lourenco et al., in press). In this study, tinnitus patients undergoing treatment were assessed through both EMA and EDD for approximately 3-months, collecting a total of 4,732 data entries from nine participants. Equivalent items assessed tinnitus experience (i.e. anger, annoyance, avoidance, distraction, fear, invasiveness, pleasantness and sadness) and wellbeing (i.e. anxiety, happiness and stress). Findings revealed a strong correlation for all items ($r > 0.68$). Furthermore, minor differences between EMA and EDD were found. EDD reported significantly more negative experiences for most dimensions (tinnitus anger, anxiety, tinnitus invasiveness, tinnitus pleasantness, tinnitus sadness and stress). Those results revealed that even short gaps between experience and reporting may create susceptibility to memory biases. In other words, recalling experiences (even from within the same day) may be perceived as worse when compared to an assessment made in the moment (i.e. "experience memory gap"; Miron-Shatz et al. 2009). Despite the differences, the authors attributed the minor variances found (all under 3.87%) to the large sample size. Generally, EDD accurately reflects the overall daily picture illustrated by EMA. As such, EDD may provide a viable alternative to EMA when burden to participants must be limited. However, EDD does not provide the rich detail of information that is only possible with EMA, specifically fluctuation within the day (e.g., like the within-day fluctuations of tinnitus described in paragraph 3 above) and pinpointing underlying mechanisms by identifying possible chain reactions in real time cannot be captured with EDD which is usually sampled at the end of the day. On the other hand, the data sampling at the of the day offers an advantage for the statistical analysis as it reduces the temporal variability in the data set; the distance between two sampling time points is usually around 24 h. Most time-series methods assume that timepoints are equally spaced, so this feature of EDD not only reduces burden, but also facilitates data preprocessing (correcting for multiple assessments within a day, correcting for non-equidistant samples). In summary, researchers could decide which method to use based on their advantages and limitations and the specific research question (i.e., shorter interventions in which variability within the day must be assessed, or interventions in which effects are expected over longer periods such as weeks or months.

16.7 Using EMA to Describe Interventions in the Single Case

The questionnaire used in the TYT study was also recently used to investigate the fluctuations and trends of the tinnitus during various clinical interventions. In this chapter we want to describe three examples where single cases were observed with the TYT questionnaire during longer periods with hearing aid use, during a self-help intervention or an acupressure treatment. In the following, we show three different EMA data sets with different analyses as an example to demonstrate the feasibility of statistical analyses on single case data, given that a large number of sampling points are available.

16.7.1 Example 1: EMA Sampling in a Hearing Aid User with Tinnitus

In this study a 56-year-old female patient with tinnitus for 5–10 years was followed in an EMA study. The patient used a hearing aid 53.8% of the time when reporting about her tinnitus and used the EMA smart phone application over a period of 4 months. Besides the daily rating of tinnitus loudness and tinnitus distress, she also recorded the hearing aid use. In Fig. 16.3 we show the fluctuation of tinnitus loudness and tinnitus distress over time. Grey areas show time ranges where the patient used the hearing aid, while white areas show time ranges where she took the hearing aid off.

Statistical comparison revealed a significant difference between the time ranges with and without hearing aid use: The average tinnitus loudness was rated 57.7 (±11.1 SD) on a scale from 0 to 100 when the hearing aid was on, and 53.9 (±11.6 SD) when the hearing aids was off. A Welch Two Sample t-test confirmed a statistically meaningful difference with $t = 2.80$, $p = 0.006$. The average tinnitus distress was rated with 48.5 (±37.5 SD) when the hearing aid was used, while the average rating was 37.5 (±16.7 SD) when the hearing was not used. Again, a Welch Two Sample t-test revealed a strong statistically significant difference with $t = 5.3$, $p < 0.0001$. Box plots are shown in Fig. 16.3.

While the statistical analysis reveals a strong relationship between hearing aid use and the subjectively perceived tinnitus symptoms, a causal relationship cannot be inferred. One interpretation could be that the patient uses the hearing aid specifically on days or specifically challenging situations where the tinnitus symptoms are higher than usual. Another interpretation could be that the particular hearing aid fitting causes the tinnitus symptoms to go up. In such a case it would be advisable to carefully adapt the hearing aid settings for this individual, i.e. adjust the hearing aid amplification in the frequency range of the individual tinnitus pitch (e.g. following Schaette et al. 2010). Also, it could be possible that a third factor influences both, the

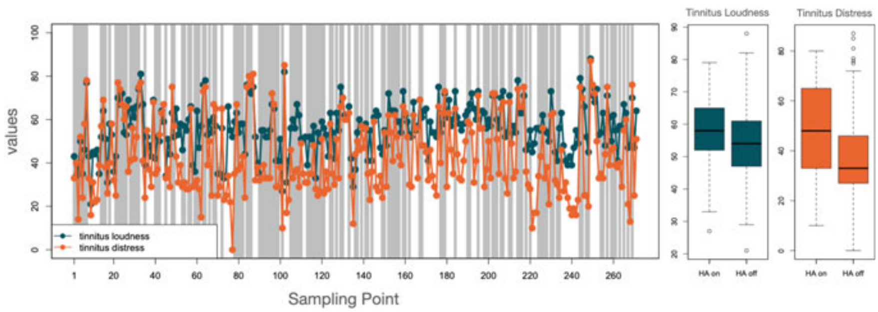

Fig. 16.3 Ecological Momentary Assessment in a hearing aid user. Grey areas show time ranges where the patient used the hearing aid; white areas show time ranges where the hearing aid was not used. Tinnitus loudness and tinnitus distress were rated higher at time points when the hearing aid was used. While the causal relationship is not clear here - this result could be an entry point for further investigations in this individual case

hearing aid use and tinnitus symptoms. This could be the case, e.g. when the patient uses the hearing aid only in certain social situations where she needs a hearing aid and if these social situations also trigger the tinnitus symptoms to increase.

In a clinical setting, such a result could be used for the next doctoral appointment where the results are discussed between the patient and the therapist to identify the causes and develop an individualized treatment strategy for a long-term reduction of tinnitus symptoms.

16.7.2 Example 2: EMA Sampling in Self-help Intervention Using an A-B-Design

The next example uses an EMA data set collected in a study with the smart phone app "TinnitusTips". This smartphone app was designed to empower the tinnitus patients by providing self-help tips for coping with the tinnitus. Every day, a new tip was displayed in the app. Within the same app, the patients were also asked about their tinnitus symptoms. With this data set, we report from a male tinnitus patient at the age of 52 years that suffers from tinnitus for more than 10 years. In the first half of the study (phase A) he used a version of the app where daily questionnaires were asked every day. At day 62, he switched into phase B of the study where the treatment with the daily self-help tips started (Fig. 16.4).

A few days after the start of the treatment with the TinnitusTips app, a drop of tinnitus distress was observed while the tinnitus loudness remained at a similar level

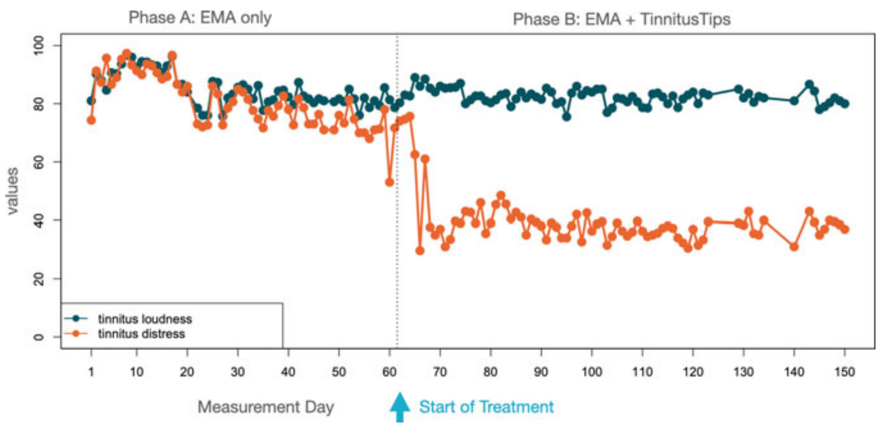

Fig. 16.4 Ecological Momentary assessment in an A-B-Design to evaluate a self-help intervention with the TinnitusTips smartphone App. In Phase A, the patient was prompted for daily measurements of the tinnitus by a smartphone app. In Phase B, a new function was added to the smartphone app: the patient received a self-help tip for dealing with his tinnitus in addition to the EMA measurements. Every day, a new tip was displayed. During phase B, the tinnitus distress decreased while tinnitus loudness was remained at the same level

like in phase A. The self-help tips that were given in the app seemed to help the patient to reduce the distress that is related to the tinnitus, while the loudness of the tinnitus was not influenced by the intervention. In phase A, tinnitus loudness and tinnitus distress fluctuated most of the times in parallel; in phase B, the perception of tinnitus loudness and distress were decoupled. For statistical analysis of this loudness-distress-differentiation, we calculated the difference between tinnitus loudness and tinnitus distress for each measurement day. In phase A, the average difference between loudness and distress was 4.5 ($\pm$5.0 SD) while the average difference in phase B was 42.8 ($\pm$8.7 SD). A Welch Two Sample t-test confirmed the strong statistical difference with a t-value $= -32.2$ and $p < 0.0001$.

16.7.3 Example 3: EMA Sampling When Using an Acupressure Device Around the Ear

In the third example we want to show an example of EMA sampling during an acupressure treatment over the course of 9 weeks. A female patient at the age of 45 years with unilateral tinnitus in the right ear and a tinnitus duration longer than 10 years. The patient reported symptoms of somatic tinnitus where the tinnitus increased with muscle tensions in the neck or jaw. For treatment, the patient was fitted with the acupressure device ForgTin, which applies a soft pressure at trigger points around the ear. Acupressure was only applied at the right ear. Tinnitus loudness and tinnitus distress were assessed daily with a smartphone app. A strong decrease of tinnitus loudness and distress was observed in the first week after start of the treatment and fluctuated at a low level in the following eight weeks as shown in Fig. 16.5.

To analyze this tinnitus development over time, a trend analysis was done for each week. A linear regression model was fitted for each week to explain tinnitus symptoms by time (see Table 16.1 for tinnitus loudness and Table 16.2 for tinnitus distress modelling). The statistical analysis confirms that the strongest tinnitus improvement occurred in the first week: the downward trend was highly significant with a slope of -1.76 for the tinnitus loudness and -1.77 for tinnitus distress in the first week; in the following weeks, there was no significant trend detected in the data.

The visual inspection and the statistical analysis both demonstrate a strong improvement of tinnitus in the first week of the acupressure treatment while tinnitus loudness and tinnitus distress kept fluctuating at low levels in the following weeks. However, a causal relationship is difficult to identify at this level. Matched control subjects or a baseline condition before the start of the intervention would be helpful to better evaluate the success of the treatment and the magnitude of the improvement.

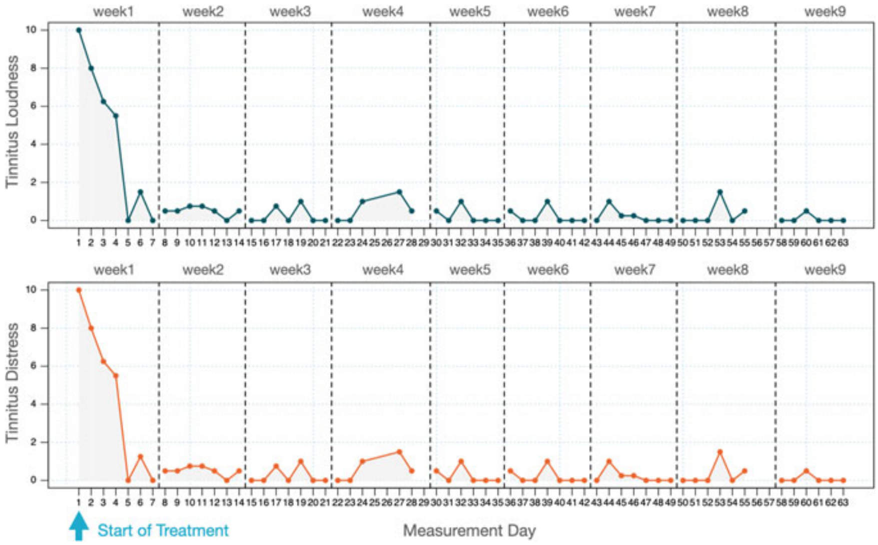

Fig. 16.5 Ecological Momentary Assessment used to investigate the tinnitus development over time when acupressure was applied to the ear daily with the acupressure device ForgTin. In this single case, tinnitus loudness and tinnitus distressed decreased in the first week and remained at low levels for the following weeks

Table 16.1 Trend analysis for tinnitus loudness over the course of 9 weeks. A linear regression analysis was calculated for each week to explain tinnitus loudness by the time (measurement day)

	Week1	Week2	Week3	Week4	Week5	Week6	Week7	Week8	Week9
Intercept	11.5***	0.99	0.09	−3.19	3.50	2.30	3.9	−5.67	0.95
Slope	−1.76***	−0.05	0.01	0.15	−0.10	−0.05	−0.08	0.11	−0.01
Adj. R^2	0.88	−0.02	−0.2	0.16	0	−0.1	0.07	−0.09	−0.23
F Value	45.6	0.87	0.01	1.75	1	0.47	1.45	0.57	0.07
p-value	0.001	0.39	0.92	0.28	0.37	0.52	0.28	0.49	0.8

Table 16.2 Trend analysis for tinnitus distress over the course of 9 weeks. A linear regression analysis was calculated for each week to explain tinnitus distress by the time (measurement day)

	Week1	Week2	Week3	Week4	Week5	Week6	Week7	Week8	Week9
Intercept	11.5***	0.99	0.09	−3.19	3.50	2.30	3.9	−5.67	0.95
Slope	−1.77***	−0.04	0.01	0.15	−0.10	−0.05	−0.08	0.11	−0.01
Adj. R^2	0.89	−0.02	−0.2	0.16	0	−0.1	0.07	−0.09	−0.23
F Value	48.1	0.87	0.01	1.75	1	0.47	1.45	0.57	0.07
p-value	< 0.001	0.39	0.92	0.28	0.37	0.52	0.28	0.49	0.8

16.8 Summary and Future Perspectives

Several independent studies have used Ecological Momentary Assessment to assess tinnitus under daily living conditions. They all revealed a considerable variability of tinnitus loudness and tinnitus distress. It has been found that emotional states and emotional dynamics, the subjectively perceived stress level and the time of the day exert influence on this variability. In these studies, the EMA method revealed potential to improve our scientific understanding of tinnitus and also showed that it can be used to understand the individual differences of tinnitus—and may even be used as a tool for individualized diagnostic and treatment. Furthermore, the results of the EMA studies can lead to improvements of existing research methods in the field of tinnitus. As shown in Chap. 7, EMA can be used to describe and investigate the tinnitus development under different treatment conditions with high temporal precision. With a reasonable amount of sampling points, it is possible to calculate robust statistical analyses even in the single case as shown in Chap. 7 of this paper.

With the rapid development of modern technology and methods in data mining, many advancements can be expected for the near future. To give two examples: Schickler and his colleagues presented 2016 a pre-study using smart watches for the EMA research (Schickler et al. 2016). They experimented with different implementations for answering questionnaire items on the limited screen space of the watch. Another example is a paper by Muniandi and colleagues applying the subspace discovery algorithm PROCLUS on the TrackYourTinnitus database to search for similarities of individual patients in the tinnitus evolution over time (Muniandi et al. 2018). Clustering of the temporal evolution of tinnitus patients offers the possibility to predict the future development of the tinnitus loudness and tinnitus distress based on the cluster membership of the patient. This method would also allow to develop an algorithm to support treatment decision for an individual patient, which is the aim in a current research project entitled "Unification of treatments and interventions for tinnitus patients" (UNIITI, Schlee et al. 2021). In this project, we are collecting EMA measurements from 500 patients that are randomized to ten different treatment arms. The data will be used to identify predictors for treatment success and to develop a clinical decision support system.

In its relatively short history—and with only a small number of researchers working on it—EMA research on tinnitus has already contributed well to a better understanding of tinnitus. More discoveries and developments are already on the horizon and we hope that more researchers will start using this promising method.

Acknowledgements R.H. is member of the Scientific Advisory Board of the UNITI project. W.S. is the coordinator of the UNITI project, member of the Scientific Advisory Board for ForgTin. W.S. and R.P. are stakeholders of the Lenox UG, which aims to translate scientific knowledge into e-health applications.

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Chapter 17
Mobile Crowdsensing in Healthcare Scenarios: Taxonomy, Conceptual Pillars, Smart Mobile Crowdsensing Services

Rüdiger Pryss

Abstract During the last years, paradigms like crowdsensing arose in the context of mobile technologies promising to support researchers in life sciences and healthcare with new opportunities. By the use of smartphones, data can be gathered in everyday life and easily compared to other users of the crowd, especially when taking environmental factors or sensor data into account as well. In the context of chronic diseases, mobile technology can particularly help to empower patients in coping with their individual health situation more properly. However, the utilization of mobile technology for healthcare purposes is still challenging, the current Covid-19 pandemic reveals it dramatically. Following this, the work at hand discusses two important and relevant aspects for mobile crowdsensing in healthcare scenarios. First, the status quo of the latter setting is discussed. Second, salient aspects are presented, which can help researchers to conceptualize mobile crowdsensing to a more generic software toolbox that is able to utilize data gathered with smartphones and their built-in sensors in everyday life. The overall goal of such toolbox constitutes the support of researchers in conducting mobile-supported studies as well as the proper analysis of this new kind of data source. On top of this, patients shall be empowered to demystify their individual health condition more properly when using the toolbox, especially by exploiting the wisdom of the crowd.

17.1 Introduction

mHealth solutions, which means to support medical and health questions/issues/aspects with mobile technology, became an enabler in supporting patients with chronic diseases in their everyday life. Smartphones can be used to remind patients to take their medication, provide them with context information, and

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*,
Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_17

foremostly, contribute to the patients' self-help as patients can monitor their condition by performing measurements, acquire insights on when the disease feels worst, and decide in a more informed way when they should ask a physician for help. Along this trend, clinicians as well as researchers try to exploit the advantages of mobile technology. As mHealth applications can gather data in everyday life and are able to easily integrate sensors (e.g., the GPS sensor to measure the walking speed) in order to collect more valuable data (e.g., by adding contextual information), *mHealth related opportunities* are more and more utilized (Kubiak and Smyth 2019, Messner et al. 2019; Pryss et al. 2019). Compared to traditional cohort recruitment methods, smartphones enable us to gather larger amounts of data in a shorter period of time (Rozgonjuk et al. 2019, Sariyska and Montag 2019, Vaid and Harari 2019). During times like the Covid-19 pandemic, many researchers and healthcare professional crave for the exploitation of these advantages. Moreover, patients often behave differently in clinical settings compared to their daily life behavior and, hence, mHealth applications can collect data in an environment that reflects the daily behavior more accurately. Although technical solutions emerged that deal with such a data collection setting like mobile crowdsensing, the opportunities, challenges, and risks are still too less considered. For example, the opportunity arises to better compare retrospective health ratings of patients with their prospective assessments (Pryss et al 2017, Pryss et al. 2018), which is often deplored in clinical settings. Especially in the context of chronic health conditions, opportunities arise that patients may be empowered to better demystify their health condition by the use of mHealth solutions. Mobile crowdsensing thereby refers to a paradigm, for which individuals collectively gather and share data with their own smart mobile devices and it is mainly characterized by two recent trends. First, mobile crowdsensing became a popular technology through the so-called bring your own device principle. Private smartphones can be easily used for meaningful sensing purposes as almost all privately owned devices have powerful computational capabilities. Second, users are more and more interested to utilize these powerful capabilities to earn money or share data for a more common interest. Technically, mobile crowdsensing mainly focuses on the assessment of large-scale phenomena by using community sensing paradigms such as (1) participatory (i.e., actively provided sensor data such as pictures) or (2) opportunistic sensing approaches (i.e., passively provided sensor data such as GPS traffic tracking) (Ganti et al. 2011).

In this context, consider the following scenario for the chronical disease *migraine*: Petra Pain wakes up late on a Saturday morning after a hard and stressful week. Since she didn't get a lot of sleep and she couldn't attend her sports class on Monday and Thursday, she decides to do some running exercises after breakfast. Unfortunately, she cannot even enjoy her breakfast neither do sports since a severe migraine attack destroys her plans. Until Sunday night, she only will be able to stay in bed, feeling dizzy, and is suffering from the symptoms of her migraine. From a friend she learns about a mobile crowdsensing mHealth application, which helps her to structure her everyday life according to her personal needs and directly gives her a specific prevention and care program based on her data. She is given help (explanation), specific exercises, and contact to other patients and specialists through the mobile crowdsensing application. When and how the help is provided depends on her situation; i.e., data is collected about her body state, surrounding situation, and routines.

To exploit mHealth as needed by a migraine patient like Petra Pain, the following questions emerge for a technical mHealth crowdsensing solution:

Q1: How to collect, accommodate, combine, and store efficiently the data entered into the smartphone, either by the patients themselves or through sensors?
Q2: How to analyze those data, taking into account that some patients do not want to share their data, while others are willing to have their data analyzed for their own benefit, for the benefit of others, or the benefit of clinical research?
Q3: How to turn those methods into smart mobile crowdsensing services, to be used both by the patients themselves and by the clinical researchers, dealing with the needs, interests, and background knowledge of both target groups?

Smart mobile crowdsensing services can particularly contribute to patient's self-empowerment, to personalized medicine, and to research on the evolution of a chronic disease. For example, the active performance of Ecological Momentary Assessments (Schlee et al. 2019, Kubiak and Smyth 2019) to capture the daily and individual moment-to-moment variability of patients and the sensing of the ambient environment can help the patients gain insights on how their symptom incidents manifest themselves and evolve, and ultimately assist them in potentially demystifying their disease. Demystification is promoted by using the smartphone recordings as basis for the patient-physician interaction: instead of describing, for example, a migraine incident the way the patient remembers it long after the incident's onset, the description will be based on a combination of objective (sensor-based) data and patient diary entries from the moments of the incident. From this information, the physicians can adjust the treatment, but can also aim at an understanding on different migraine profiles.

To unravel these opportunities, smart mobile crowdsensing services should aim at a data-driven collection procedure that can be used by (1) researchers as well as (2) patients and health care professionals. To enable this, a proper mobile crowdsensing toolbox should be built on three fundamental considerations:

First, the toolbox that shall be developed must be based on the requirements and needs of patients, health care providers as well as researchers. In this context, a data model must be derived that serves as a basis for a new data pool that stores data gathered by smartphones in everyday life. Following this, it must be investigated how existing data analysis methods can be applied to this data pool or whether new data analysis methods become necessary.

Second, the toolbox must comprise smart mobile crowdsensing services, which are based on real-life data gathered for patients suffering from chronic diseases such as migraine. Those patient groups are particularly interesting for clinical research since the health state of these persons is highly dependent on external factors of the personal environment and on internal factors of the body that can be measured by changes of several clinical indicators (i.e., via mobile technology and sensors).

By using mobile sensor technology and high-end data analysis methods, a broad spectrum of situation-based data (including the moment-to-moment variability) can be collected and used as a basis for the development of preventive or curative health care services.

Third, as mobile applications are technically dependent on many factors (Schickler et al. 2015; Schobel et al. 2017), the smart mobile crowdsensing services should be realized as a sustainably specialized IT solution in the context of chronic conditions, patient self-empowerment, life sciences, and the opportunities arising with the proliferation of mobile technology. Consequently, if the functionality is bound to several smart mobile crowdsensing services instead of a particular mobile health application, gathered data can be compared more easily to other types of data sources (e.g., clinical-driven data collection).

The present chapter provides an overview on this important topic, subdivided into six sections organized as follows. In the next section, current research on mobile crowdsensing is discussed. Then, the section *Taxonomy* discusses mobile crowdsensing in healthcare scenarios compared to existing approaches. In the sections *Conceptual Pillars of Smart Mobile Crowdsensing Services for Healthcare Scenarios* and *Development of Smart Mobile Crowdsensing Services for Healthcare Scenarios,* important technical foundations are presented. Finally, section *Flip Side* discusses relevant drawbacks identified in practice, while section *Summary & Outlook* concludes the findings and provides an outlook on future work.

17.2 Related Work

Extant research that is relevant in the context of this work constitutes mobile crowdsensing in the medical domain as well as works that deal with mobile crowdsensing enabling Ecological Momentary Assessment (EMA; also known as ambulatory assessment & experience sampling) methods (Trull and Ebner-Priemer 2013; Schlee et al. 2019, Kubiak and Smyth 2019). Mobile crowdsensing is still an emerging research topic in various application domains (Luo et al. 2017; Shu et al. 2017). In the healthcare domain, however, this research direction has been only little picked up so far. The fact that the healthcare domain is less considered by contemporary crowdsensing approaches might be explainable by legal and data privacy issues (Christin et al. 2011). Nevertheless, mobile crowdsensing offers promising perspectives for the medical domain (Ganti et al. 2011), as it exhibits unique features for gathering valuable patient data in the large scale (Demirbas et al. 2010). In particular, mobile crowdsensing allows for the effective, context-aware gathering (Ma et al. 2014) of daily-life patient data (Probst et al. 2016), which, in turn, may shift clinical research to a new level. Furthermore, some recent works exist that deal with generic crowdsensing approaches to enable human-subject studies (Xiong et al. 2016).

Furthermore, apart from mobile crowdsensing solutions, mobile applications have been presented that incorporate EMA-measurements with valuable healthcare results.

In particular, EMA approaches are used to capture various aspects such as pain or feelings in daily life. Although most mental health symptoms are subjective experiences and, thus, most EMA approaches use self-reports to capture these symptoms, some symptoms are behavioral (e.g., avoidance in anxiety disorders) or physiological (e.g., increase of heart rate in anxiety disorders). Especially in this context, mobile applications offer powerful opportunities to measure behavioral or physiological data in daily life (Ebner-Priemer and Kubiak 2007; Sariyska et al. 2018; Montag et al. 2019).

In addition, the 2016 for the first time presented concept of digital phenotyping also translates EMA-measurements into the mobile and digital world. Digital phenotyping is mainly based on the idea to gather data from users in their natural environment based on digital devices, while capturing the moment-by-moment situations of the users in situ (Onnela and Rauch 2016). Although digital phenotyping could be put on a level with digital EMAs, it must be decided from case to case how the digital phenotyping is designed by an approach in question. If an approach adheres to the definition that was initially provided by Onnela and Rauch 2016, then this approach can be put on a level with digital EMAs. Pertaining to mobile crowdsensing, the passive and active data sources that were described by the authors of digital phenotyping correspond to the participatory and opportunistic sensing concepts of mobile crowdsensing. On the flip side, differences between digital phenotyping and mobile crowdsensing should be carefully considered (see Category 4, Section Taxonomy).

Altogether, EMA-driven approaches provide unprecedented opportunities to study mental health symptoms and life science factors under ecologically valid conditions (Myin-Germeys et al. 2009), even though the integration of EMA-related possibilities into mobile crowdsensing solutions is still in its infancy, especially in the medical/healthcare domain. However, as mobile crowdsensing and EMA have already revealed valuable insights for tinnitus (Probst et al. 2016; Schlee et al. 2019, Kubiak and Smyth 2019) and provided help in the context of pregnancy (Ruf-Leuschner et al. 2016), the investigation of mobile technology for life sciences and the medical/healthcare domain is promising. In particular, new data pools, new evaluation methods, and algorithms as well as related tool developments are promising outcomes when investigating this technology in a more in-depth manner. A recent work discusses the combination of mobile crowdsensing and EMAs from a healthcare perspective based on multiple project insights (Kraft et al. 2020) in a very comprehensive manner and with many provided guidelines.

17.3 Taxonomy

Prior to considerations how smart mobile crowdsensing services can be realized for healthcare scenarios, another important aspect must be introduced, i.e., the way how mobile crowdsensing has been hitherto characterized in literature and existing technical solutions. Currently, existing works divide mobile crowdsensing into one of the following two categories: Either a (C1) participatory or an (C2) opportunistic

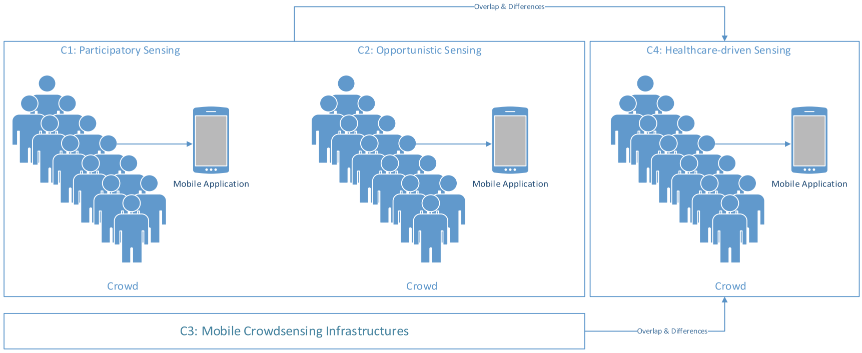

Fig. 17.1 Mobile crowdsensing taxonomy including healthcare scenarios

sensing approach is pursued (Ganti et al. 2011; Ma et al. 2014). However, most extant research works do no put their crowdsensing approaches into C1 or C2, and rather describe realized technical infrastructures and their benefits (C3) (Xiong et al. 2016). A brief introduction into C1-C3 will be given in the following and, on top of this, it will be shown that mobile crowdsensing in healthcare scenarios cannot be put directly into C1-C3. Consider therefore Fig. 17.1, in which the so-called healthcare-driven mobile crowdsensing approach is proposed in addition.

The three existing approaches C1-C3 pose the following characteristics:

Category 1: Participatory Sensing (C1): Sensing tasks (e.g., measure sound level at a certain location) are advertised through a crowdsensing platform and crowd users that are bound to this platform deliberately opt for accomplishing these tasks. Main goal of the participatory sensing is to find the most suitable crowd user for a sensing task in a reasonable period of time. Crowd users either get an incentive to take over such tasks (e.g., by getting money), or want to serve the society by accomplish sensing tasks for a common interest (e.g., by gathering data that can be used to create a noise map for hearing-impaired people).

Category 2: Opportunistic Sensing (C2): Opposed to the participatory sensing, here, crowd users do not deliberately take over sensing tasks, they rather install a crowd-sensing software on their smartphone, which collects data in an automatic and user-unconscious fashion and sends it to a crowd server. Beside the latter mentioned aspect, opportunistic sensing follows the same goals like C1.

Category 3: Mobile Crowdsensing Infrastructures (C3): There exist several approaches that do not explicitly distinguish whether their realized infrastructure follows the participatory or opportunistic sensing paradigm, they rather describe how a crowdsensing infrastructure or parts of it can be efficiently developed. For example, in the work of (Xiong et al. 2016), it is described how an infrastructure could look like to support human-subject studies. Another example is the sharing of GPS-based traffic information to better cope with congestions or other vehicle-related aspects (Wan et al. 2016).

In turn, the new approach C4 poses the following characteristics:

Category 4: A new paradigm for crowdsensing in health care (C4): To justify that this category should be separately considered, it is illustrated that the basic goals of the existing approaches C1-C3 differ significantly compared to C4. To be more specific, approaches that follow C1-C3, mainly address the following goal: Sensing tasks exist (predefined number and normally predefined locations) and the question must be answered, how a suitable crowd user can be found and selected to accomplish these tasks in the best possible way (in most cases, this means in a timely manner or inexpensively). As a direct effect of this goal, it is not important who actually accomplishes a sensing task, it is rather important that the crowd is utilized in the best possible way for upcoming sensing tasks. As an example, it is crucial to find the closest crowd user for a task to sense the temperature at a certain location. Following this, a fundamental research question of approaches following C1-C3 is to investigate and develop recruitment methods for a sensing task (e.g., Karaliopoulos et al. 2015). Therefore, a proper user motivation or an efficient incentive management are major research targets in this context. Another definition would be that the sensing tasks can be seen as a trade currency, which is utilized by the crowd users as well as the crowdsensing platform vendors to pursue one of the two aforementioned goals. Moreover, for C1-C3, the sensing tasks are externally defined, both for the task itself (the measurement instrument) as well as the time and location.

In mobile crowdsensing healthcare scenarios, in turn, the direction of how sensing tasks are related to executing crowd users is very different. Here, the main goal is that crowd users are the important target and the two main questions arise, (1) how sensing tasks are provided to the crowd users, and (2) which data aspects are correlated and actually evaluated. Furthermore, the user in question defines the time and location him- or herself. Even the measurement instrument is defined by the users themselves, at least to a certain degree of freedom in most cases. In other words, in healthcare-driven mobile crowdsensing scenarios, the initial considerations do not start with the sensing task, they start with the crowd user and it is then determined, how a user accomplishes sensing tasks. As another fundamental difference of C4 compared to C1-C3, in most cases, a crowd user shall continuously accomplish the same sensing task to investigate within-day and day-by-day variations of the same sensing task. This shall help to (1) monitor an individual crowd user over time, and to (2) enable comparisons with other crowd users that have a similar evolution. For approaches that follow C1-C3, in turn, crowd users opt for different sensing tasks, without pursuing the goal to continuously accomplish the same sensing task again and again. Based on the fundamental difference, i.e., whether the sensing task or the crowd user is the starting point, the addressed research questions differ respectively. For example, in scenarios related to C4, motivation means to find solutions that crowd users do not leave the platform, while in approaches following C1-C3, motivation means to find solutions to increase platform usage in general. Finally, note that although several aspects between C1-C3 and C4 differ, there are also many aspects that overlap each other. For example, proper infrastructures are required for C1-C4. Furthermore, security aspects play an important role in all categories as well. Having in mind that there is a profound difference in using mobile crowdsensing for healthcare scenarios, the considerations for respective smart services can be better aligned to the pursued goals in this context.

17.4 Conceptual Pillars

The presented concept for smart mobile crowdsensing services in healthcare scenarios is given by the following existing and ongoing projects: TrackYourTinnitus (Tinnitus) (Pryss et al 2017-2), KINDEX (Pregnancy) (Ruf-Leuschner et al. 2016), https://www.trackyourhearing.org (Hearing Loss), https://www.trackyourstress.org (Stress), as well as the involvement in studies on diabetes patients in Bulgaria and Spain (EU Grant Agreement Number 761307). Based on this groundwork, the proposed smart mobile crowdsensing services are built on the following conceptual pillars: (1) The development of a proper crowdsensing collection procedure for healthcare scenarios, (2) the knowledge about data sets in this context, and the (3) behavior patterns of patients and users in such a collection setting. Regarding Pillar (1), consider Fig. 17.2, it reflects the crowdsensing collection procedure being revealed in the aforementioned projects. This procedure essentially aims at three goals: First, data shall be collected on a daily basis (see Fig. 17.2, 4). However, a user shall not foresee the times he or she is asked to sense data (see Figs. 17.2 and 17.3). This is ensured by asking the users in various daily life situations. Second, the collected data shall enable new kinds of data analysis like juxtaposing real-time assessments and retrospective reports (see Figs. 17.2 and 17.3; (Pryss et al 2017, Pryss et al. 2018)), or evaluating the different assessment times of a day (Probst et al. 2017). Third, gathered data shall be used to provide feedback to the mobile crowd users. Although the conducted projects revealed that a structured collection procedure as shown in Fig. 17.2 is indispensable, its systematic use is still neglected

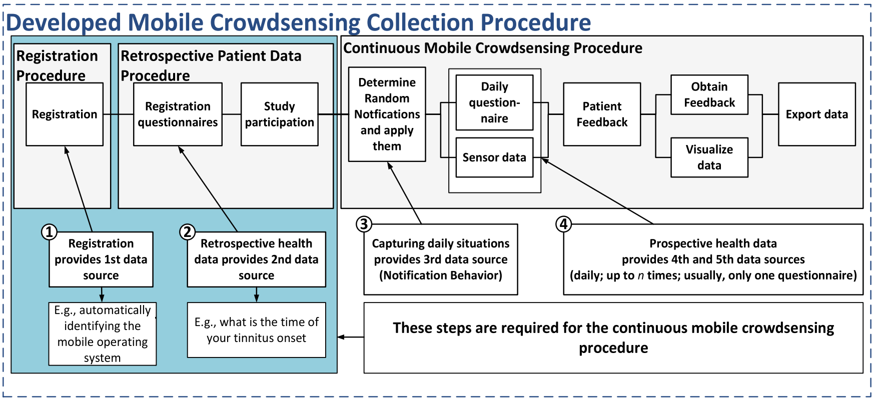

Fig. 17.2 Developed mobile crowdsensing collection procedure

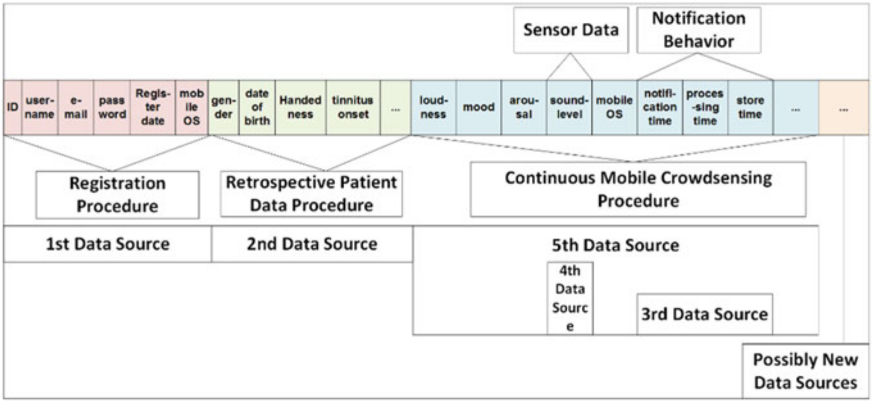

Fig. 17.3 TrackYourTinnitus crowdsensing data structure

and less understood. However, a systematic and structured use would enable a more generic utilization as well as allow for more flexible collection procedures in this context, thus potentially leading to more valuable data and analysis opportunities. Furthermore, data pools gathered by the use of mobile crowdsensing could be better compared based on the presented collection procedure.

As can be also seen in Fig. 17.2, a mobile crowdsensing collection procedure reveals different possibilities to establish valuable types of data sources. For example, a data source that reflects retrospective data (i.e., a retrospective assessment of a patient), and one that reflects prospective data (i.e., a prospective assessment of a patient when being asked in a daily situation or on future outcomes) can be established and compared. Taking the different types of data sources into account, while considering Pillar (2), the used data structure is important for the development of smart mobile crowdsensing services. Therefore, consider Fig. 17.3, it shows an example for a data structure used in the aforementioned projects, which is based on the collection procedure shown in Fig. 17.2. When mobile crowdsensing data is collected along such data structure, new data pools can be established, which, in turn, may reveal valuable medical insights of a crowd user over time. Regarding the development of new data pools in this context, consider the following realistic example: For a migraine patient, several data sets can be gathered utilizing the procedure shown in Fig. 17.2, when actually following daily measurements. Let us assume that 12 gathered data sets each day are realistic and not too burdensome for a migraine patient. Then, when multiplying this with 7 days a week, and 52 weeks a year, eventually, for one migraine patient, possibly 4368 data sets become possible. If one thousand crowd users are applying this procedure in the context of their migraine situation, it can be assumed that in one year, with only 1000 users, 4,368,000 potential data sets (i.e., each including all the information shown in Fig. 17.3) become possible. However, many other evaluations become possible, e.g.:

- Juxtaposing retrospective assessments of patients with their daily assessments.
- Evaluating user behavior of different mobile operating systems compared to their provided data.
- Comparing users with similar and different sociodemographic (e.g., gender, age, education, nationality, ethnicity) and clinical characteristics (e.g., disease status, chronicity, disease progress, comorbidities) to provide benchmark and prediction models.
- Adding sensor data to the gathered patient data and compare subjective assessments with more *objective* assessments.
- By changing the data collection procedure, it can be observed how patients may change their behavior accordingly.
- Gathering longitudinal medical data in a more efficient way, especially without the potential bias of experimenters, compared to traditional clinical trials.

Comparing this structured data amongst all users (for those who share personal anonymous data sets with others), or in a longitudinal study for single users (for those who only track their own personal data sets), allows for the development of preventive and care services that are custom-fit for individual users based on the power of the crowd. Finally, Pillar (3) allows for the analysis of behavior patterns of users in this context, tailored to the questions of researchers. For example, when the first data is collected for a migraine patient, it might be the case that a patient may lose interest to provide data, or using the technical solution in general. In this case, an incentive management (e.g., by the use of gamification aspects) becomes necessary for the smart mobile crowdsensing services (e.g., Agrawal et al. 2018).

17.5 Development Phases

In the previous section, conceptual pillars for the development of smart mobile crowdsensing services in healthcare scenarios were illustrated. In this section, the development phases that have been identified to realize such services in practice are presented. Prior to this, it is shortly sketched what technical components should always be assumed for a mobile crowdsensing platform in healthcare scenarios. In the mobile crowdsensing projects that have been realized as the basis for the work at hand, six fundamental technical components have been identified to be a proper basis to enable a useful mobile crowdsensing platform for healthcare scenarios. At first, an (1) Android as well as an iOS mobile app must be developed to gather data. Principally, also platform-independent approaches for realizing the apps are a conceivable solution. However, as sensor measurements are often performed in healthcare scenarios, which need mobile operating system calls, native apps should be preferred. Second, these apps must be connected to a (2) flexible API (e.g., RESTful in our case; cf. Pryss et al. 2018-2) that governs the communication with (3) a central database (relational or NoSQL), to which the data is stored to. Fourth, (4) a web application should be developed, which can be used by the crowd users, researchers as well as healthcare professionals to investigate and visualize the collected data. In addition, the website can be used for further administration needs (e.g., user management). Fifth, (5) a sensor component must be realized, which handles the collection of sensor data. Finally, (6) a feedback component should be developed that enables healthcare professionals and researchers to send feedback to a mobile crowd user. To get a better insight into such components, for the TrackYourTinnitus project, they are described in (Pryss et al. 2015). Note that these components are the basis to offer smart mobile crowdsensing services based on the conceptual pillars shown in the previous section. In order to realize the technical components practically, the following six development phases have been identified, to be accomplished in the shown order:

Phase 1—Requirements and Needs: In this phase, the relevant roles (e.g., patients, researchers, doctors), their requirements (e.g., support of Android and/or iOS smartphones), and their needs (e.g., notification algorithms) must be identified and assessed.

Phase 2—Crowdsensing Collection Procedure: In this phase, the mobile crowdsensing collection procedure must be defined, with the help of researchers as well as the healthcare professionals (e.g., medical doctors or psychologists).

Phase 3—Data Model: A data model (i.e., the data structure) that drives all phases of the mobile crowdsensing collection procedure must be defined. In addition, a quality model should be defined over the data model, including a codebook for later data analysis purposes.

Phase 4—Data Analysis Methods: All functions to be used for the later data analysis must be defined. For example, exploiting patient similarity could be a research question that shall be dealt with. Therefore, it must be defined whether existing methods can be used or new methods become necessary.

Phase 5—User App Journey and Synchronization Procedure: In this phase, based on the outcomes of Phases 2–4, two procedures must be defined. **First**, the so-called user journey for the app usage must be determined. That means, the dialogue structure (i.e., the provided user views and their logical interdependencies) for using the mobile apps based on the specified mobile crowdsensing collection procedure must be defined. For the TrackYourTinnitus project, the user journey can be found in Agrawal et al. (2018). To this end, the user journey translates the mobile crowdsensing collection procedure into a procedure that users have to follow when using the mobile crowdsensing apps. **Second**, the synchronization procedure must be defined, i.e., the strategy at which points in time a mobile crowdsensing app synchronizes its collected data with the central database through the flexible API. In addition, it must be defined whether the collected data is only stored into the central database or also locally stored on the mobile crowdsensing apps. Finally, it must be defined how data is cached on the mobile crowdsensing apps. Caching becomes necessary if an app has no internet connection for a longer period of time. For the TrackYourTinnitus project, the synchronization strategy can be found in Kraft et al. 2020. In addition, the synchronization procedure is a crucial point for ad-hoc analyses that shall be directly performed on the smart mobile devices of crowd users. For example, if a crowd user wants to compare his or her assessments over the last week with other crowd users, it must be determined, which data should be considered for a comparison.

Phase 6—System Evaluation: In this phase, an evaluation service must be developed, which is the fundamental pillar of a service quality framework. The latter shall provide features to be able to continuously monitor the smart mobile crowdsensing services over time.

If the considerations of the previous section are taken into account during the presented six development phases, then, the six technical components discussed in the beginning of this section can be realized in a way that they can actually provide smart mobile crowdsensing services for healthcare scenarios in a flexible and powerful way. For the TrackYourTinnitus project, a selected service that takes all these considerations into account—namely, the patient feedback service—can be found in (Pryss et al. 2017-2).

Finally, the crucial points of the three presented technical sections are summarized, which are the basis to enable helpful mobile crowdsensing services for patients like the fictive case of Petra Pain, as illustrated in the Introduction section.

It was elaborated that the experiences of the performed practical implementations of several crowdsensing platforms have revealed that the offered crowdsensing features should be bound to smart mobile crowdsensing services. It was shown that mobile crowdsensing in healthcare scenarios is different in its nature to non-healthcare scenarios. The revealed conceptual pillars for the smart mobile crowdsensing services were presented. They take the nature of healthcare aspects particularly into account. Furthermore, the development phases and technical components that are necessary to practically realize these services were shown. For the conducted mobile crowdsensing projects, these aspects were key success factors to maintain and evolve a mobile crowdsensing platform for healthcare scenarios over time. A recently proposed mobile crowdsensing infrastructure that offers sophisticated mobile crowdsensing services for a healthcare scenario can be found in Kraft et al. 2019.

17.6 Flip Side

In this paper, the use of mobile crowdsensing services in healthcare scenarios have been discussed. As shown, mobile crowdsensing can be an enabler for EMAs on smartphones, also called digital phenotyping in other contexts. As EMAs are characterized by the fact to gather ecologically valid data through capturing users in situ, this kind of collected data surpasses many drawbacks of clinical study settings. For example, EMA-driven collected data minimizes the retrospective bias. However, there are many downsides that must be also carefully considered. The major ones will therefore be summarized. They have been identified by the projects this work is based on (see section Conceptual Pillars).

(1) As iOS and Android differ in several regards, which is often only apparent to the application developers, it must be ensured that collected data sets are 100% comparable.
(2) On top of (1), there exist a vast number of smartphone vendors, which often change their contracts with sensor manufacturers. Thus, it must be ensured that all measured sensor values are comparable. For example, are microphone measurements of two smartphones really the same?
(3) On top of (1 + 2), are the user interfaces on different mobile operating systems 100% comparable? If not, users might by differently attracted or distracted.
(4) In addition to (1 + 2 + 3), it should be thoroughly tested whether the smartphone data is reliably stored at the backend for data analysis purposes. For example, are all time stamps, i.e., the ones created by a smartphone and the server and other smartphones, 100% comparable?
(5) Users have different possibilities to fool the system. For example, users can be bothered by notifications on the one hand, but dutiful to the system on the other hand. That means, it should be checked whether measurements have been only performed to satisfy the system to fulfil a duty. Or, as another possibility, users want to compete with other users and gather too much data that do not reflect their daily in situ situation.
(6) Both, data-driven methods (e.g., algorithms that detect inaccurate data) as well as app features (e.g., how questions are articulated) should be investigated and implemented, with the goal to identify or prevent fooling opportunities of the system like mentioned in (5).

The discussed aspects affect the validity of data collected with mobile technology and mobile crowdsensing services in healthcare scenarios. Therefore, more and more works try to investigate whether the technology itself provides meaningful data sources (e.g., Weierstall et al. 2021). In addition, another research field emerged in the last years in this context, which considers the quality of mHealth apps in general, mainly based on particularly developed questionnaires like presented by Stoyanov et al. (2015). Works in this field foremostly focus on aspects of the appearance and usability of mHealth apps. Indirectly, aspects like the crowdsensing collection procedure are addressed by these approaches through combined usability aspects that are investigated. The way mobile crowdsensing is technically designed, however, draws a much broader picture when being used in healthcare scenarios. Ultimately, the mentioned worlds (mobile crowdsensing, EMA, digital phenotyping, etc.) are linked through many aspects, but differ also in many major goals. Therefore, when designing mobile crowdsensing services for healthcare scenarios, the implementation team should always be aware of a complex setting with many potential obstacles.

17.7 Summary and Outlook

The work at hand discussed mobile crowdsensing technology in the context of chronic diseases in particular and healthcare scenarios in general. To this end, three findings that were discussed along the conducted projects are of particular importance. On the one hand, mobile crowdsensing can enable substantial data sources that may lead to new insights for a medical condition or be the basis for patients and health care providers to understand patients´ individual health condition and disease courses in a better way. On the other hand, from a more technical perspective, two findings are important. First, mobile crowdsensing, when used in healthcare scenarios, poses different characteristics to non-healthcare scenarios. This refers particularly to the relationship between sensing tasks and crowd users. To be more precise, in healthcare scenarios, sensing tasks do not exist a priori like for the well-known participatory and opportunistic crowdsensing paradigms. Rather, the sensing tasks are decided by the crowd users themselves. In addition, in healthcare scenarios, results of the sensing tasks of crowd users are compared over time, which is, again, not important for the aforementioned well-known sensing approaches. Second, if mobile crowdsensing shall be used as a generic toolbox in healthcare scenarios, many considerations are necessary, which are still too little addressed. In particular, the presented considerations on the mobile crowdsensing collection procedure are decisive aspects. Altogether, it can be argued that the opportunities surpass the drawbacks and therefore mobile crowdsensing can play an important role in healthcare scenarios. Future efforts of our work mainly address more powerful configuration opportunities for the smart mobile crowdsensing services on the one hand. On the other hand, incentive management features with the goal to prevent crowd users to early leave a mobile crowdsensing platform will be a main research focus, including suitable feedback features. Successfully implemented, combining ecological momentary assessments and smart sensing possibilities for individuals with the power of crowd-knowledge (i.e., cross individual sensing), will ultimately improve insights into diseases and their individual courses, allowing for, for example, just-in-time interventions, which are tailored to the specific needs of individual patients.

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Chapter 18
mHealth Applications: Potentials, Limitations, Current Quality and Future Directions

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Abstract Due to the constant use of smartphones in daily life, mHealth apps might bear great potential for the use in health care support. In this chapter the potentials, limitations, current quality and future directions of mHealth apps will be discussed. First, we describe potential benefits like quicker facilitation of information, patient empowerment and inclusion of undersupplied population groups. Furthermore, the use of mHealth apps for diverse somatic and mental health conditions will be discussed. Beyond, the chapter provides the reader with a short overview on the efficacy of mHealth apps for different indications: Exemplary, we provide evidence for the efficacy of mHealth apps in the realm of asthmatic disease, depression and anxiety disorder. Despite the availability of mHealth solutions, the acceptance of among health care providers is still moderate to low. This represents a substantial problem, as health care providers are important gate keepers for intervention uptake. In this context we describe methods to foster acceptance. Furthermore, we address potential risks of mHealth app use including low responsiveness towards critical situations (e.g. self-harm) or the difficulty for users to assess the quality of the app's content. Here we refer to standardized instruments to assess app quality. With respect to the massive amount of sensitive data already being collected through such mHealth apps, we also reflect on the latest current legal situation in Europe and the United States.

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_18

18.1 Current Use of Smartphones

Smartphones are an integral part of daily life. They are widely used all over the world with around 65% owning a smartphone in Europe and America and 33% worldwide (Donner 2008). Especially in developing countries the number of smartphone owners is rising, resulting in major social and economic changes (Marcolino et al. 2018). Given the ubiquitous availability of smartphones, the health care sector might profit from their large distribution. In this context, especially the developing countries have hope, that mHealth apps can complement their routine care while reducing costs (Beratarrechea et al. 2014; Donner 2008; Gurman et al. 2012). In general younger individuals are more likely to own a smartphone than older, leading to diverse digital behaviour across generations (Albrecht 2016). A study from Germany demonstrated that the average person between 15 and 35 years carries the smartphone around all day and spends an average of 162 min using it, thus making smartphones a great opportunity to track behaviour in real life (Montag et al. 2015) particularly in the younger generation at present.

In the context of the present work, it is of interest, that currently 325.000 mHealth apps are available in the app stores (Research2guidance 2016; Statista 2019). The explosion in the number of available mobile health apps is mainly due to their economic profitability: The turnover has quintupled to $23 billion since 2013. The (scientific) assessment of available apps, their potential and limitations as well as app quality and data security issues for end-users and practitioners is therefore as challenging as urgently needed in this rapidly growing secondary healthcare market.

18.2 Current Use of mHealth Apps

Around 60% of smartphone users have at least one mobile Health app (mHealth app) installed and around 76% of individuals report interest in using their smartphone to monitor and improve mental health (Proudfoot et al. 2010). In the last four years the number of downloads of mHealth apps has doubled, indicating a rising acceptance of mHealth app use (Research2guidance 2016). Users of mHealth apps report to use the mHealth app for recording of body and fitness data (27%), educational purposes related to health (20%), to assist in behaviour/lifestyle modification (11%) and to improve health management regarding medication and vaccination (2%). Krebs and Duncan (2015) found that in America 58% have downloaded a mHealth app and used it on a daily basis. In their sample mHealth app users were younger, had higher income and a higher educational status. The most common categories of app use were fitness and nutrition.

There are no gender differences in the frequency of mobile health app use (Albrecht 2016). People between the age of 18 and 29 use mobile health apps the most, people between the age of 30 and 59 use mHealth apps moderately, whilst persons above the age of 60 rarely use mHealth apps at the moment (Albrecht 2016).

Since elderly people are prone to chronic disease, they have a higher need of support which might not always be covered comprehensively by health care professionals, resulting in the potential use of mHealth apps to empower elderly patient's self-help abilities. Hence, the training of technology literacy particularly for the elderly could be promising to complement traditional care systems (Singh et al. 2016). Moreover, the age threshold of mHealth app use most probably will further increase with the next generation of elderly who by then will already show substantial mHealth literacy. Hence, digital natives will probably more easily embrace this new (self-help) intervention approaches.

18.3 Potential Benefits of mHealth Apps

MHealth apps have the potential to transform the way health services are delivered by quicker facilitation of health information (Marcolino et al. 2018). Future health care systems will rely on synchronized care processes shared by diverse care givers, resulting in the need of embedded broad information systems. Furthermore, patient empowerment (e.g. seeing the patient as a major driver of documentation, healing and health behaviour) will be emphasized in the future (Nasi et al. 2015). Those developments could be assisted through mHealth technology. Moreover, there is great potential for new app technologies, because population groups currently being undersupplied might profit from their use. Among these are people from rural areas, people from developing countries, children and adolescents, elderly people, disabled people and minorities (Donner 2008; Marcolino et al. 2018; Singh et al. 2016). Mobile health apps could be used independently of geographical situation, language abilities and further barriers to treatment. They can be used as assistance in clinical diagnostics, for the assessment of disease course, in blended therapy settings, as self-help tool while waiting for routine care or in relapse prevention (Baumeister et al. 2017; Ebert et al. 2018; Rathner et al. 2018a). Assistance in diagnostics and measurements of change can be achieved through active user input or passive behavioural tracking (Rathner et al. 2018b; Sariyska et al. 2018). Furthermore, they could complement standard care by giving less stigmatized access to therapeutic content or medical treatment (Bloomfield et al. 2014; Torous et al. 2014).

Moreover, there is evidence from systematic reviews that mHealth apps can help to improve treatment adherence overall and especially in chronic or stigmatized disease management (Beratarrechea et al. 2014; Bloomfield et al. 2014; Hamine et al. 2015; Marcolino et al. 2018). Such improvements in adherence are rooted in the embedding of interventions into everyday life by using real-time situation triggered reminders, pushes and notifications (Marcolino et al. 2018). In addition, mobile health apps offer the opportunity for real-time interventions (e.g. triggering a breathing exercise in case of acute need) and for automated data input (e.g. passive tracking of smartphone usage behaviour, movement data, sleeping times) as well as manual data input (e.g. mental state, homework) (Kubiak and Smyth 2019; Rabbi et al. 2019).

Furthermore, people with chronic diseases represent a significant target group. People suffering from chronic conditions can benefit in a great extent from lifestyle changes with regard to the prospective disease process. Moreover, it might be cost-effective if individuals with high treatment needs and corresponding high treatment costs would use (blended) internet-and mobile based interventions (IMIs) (Bendig et al. 2018; Singh et al. 2016). In this sense IMIs also might help to empower patients to a self-determined health management (Bendig et al. 2018). The use of mobile health apps verifiably leads to higher levels of autonomy and increase perceived self-efficacy. Mobile health apps have the potential to assist people with and without clinical diagnosis to promote desired behaviours (Bakker et al. 2016).

The use and the prescription of mHealth interventions might be of particular interest, as patients believe that these apps could improve quality of care through better communication (Krebs and Duncan 2015). Moreover, from a patient's perspective, other domains of mHealth apps are of relevance. Individuals with mental health needs report, that they think content (90.8%), ease of use (89.6%), cost (79.2%), encryption (74.2%), interactive features (73.7%), customization (70.9%), privacy policy (70.5%), direct and indirect research evidence (68.1%), simple language (60.7%), user ratings (59.4%) and user reviews (58.7%) are important in mHealth adoption. Furthermore, burdened individuals highlight, that they value ease of use (27%), visual appeal (18.2%), simple language (17.4%) and content (14.4%) in mHealth apps they already use (Schueller et al. 2018).

18.4 Evidence on the Efficacy of mHealth Apps

Worldwide mHealth apps are mainly used for patient communication, monitoring, education, for disease management, to facilitate health services, to improve clinical diagnostics, to foster treatment adherence and for the management of chronic diseases (Devi et al. 2015; Gurman et al. 2012). Although they are widely used and there is a common belief that mHealth apps can improve the quality of care, lead to a reduction in costs and can be adapted on large scale, strong evidence on the effectiveness and cost-effectiveness is still lacking in most areas (Ebert et al. 2017). Note that this lack of evidence is specific for mHealth, while there is strong evidence for the effectiveness and cost-effectiveness of Internet-based (therapeutically guided) self-help interventions (Bendig et al. 2018; Domhardt et al. 2018; Ebert et al. 2018; Paganini et al. 2018).

In a systematic review of systematic reviews, Marcolino et al. (2018) came to the conclusion that mHealth apps are helpful for individuals who suffer from asthmatic disease in regard to a better symptom control, decrease in medication, increased treatment adherence and a reduction in hospitalizations when compared to a treatment as usual control group. Patients in cardiac rehabilitation profit from mHealth app use with respect to their exercise capacity as well as in reduction of blood pressure and body mass index. Patients with congestive heart failure reported fewer symptoms and their relative risk of death or hospitalisation decreased, while their quality of life increased when using mHealth interventions. Individuals suffering from diabetes profited in various bio-parameters such as HbA_{1c}, cholesterol and microalbuminuria. The treatment adherence and viral load of people suffering from HIV could be improved by using mHealth apps. Regarding lifestyle changes including promotion of physical activity, smoking cessation and safe sexual behaviour mHealth seems promising, too. However, the latter assumption relies on an expert opinion rather than on empirical evidence (Marcolino et al. 2018).

Firth et al. (2017a) conducted a meta-analysis on randomized controlled trials (RCTs) of depression mobile apps. They showed that depressive symptoms decrease significantly when using a mHealth app when compared to active (e.g. treatment as usual) or inactive (e.g. waitlist control) control groups. MHealth Apps focusing on improvement of general mental health were superior to those focusing on cognitive training. These results indicate that mHealth apps are a promising self-help tool to manage depression. In another meta-analysis and systematic review Firth et al. (2017b) found that mHealth apps are also beneficial for individuals suffering from anxiety disorders. Taken together these findings build a solid body of evidence for the efficacy of mHealth apps in specific disorders and point towards possible efficacy in others. The mechanisms of change while using mHealth interventions are still unknown (Domhardt et al. 2019) and might stem from factors in the individual, characteristics of the mHealth app and general attitudes of the socioeconomic system.

18.5 Acceptance of mHealth Apps in Health Care Providers

Despite the positive findings on the effectiveness of mHealth apps there is moderate to low acceptance towards the use of mHealth apps among health care providers (Krebs and Duncan 2015). This represent a highly relevant problem since end users (here patients) can be influenced by expert opinions (East and Havard 2015). The acceptance of mHealth apps depends on the characteristics of the intervention as well as internal factors related to the patient (e.g. knowledge, competences and attitudes) and external factors (e.g. policy, health care, technical and institutional resources, attitudes of the social system) (Liu et al. 2014; Phillips et al. 2015). Health care providers are mainly concerned about data security and low responsiveness towards critical situations (e.g. reactivity if a person is self-harming or a hazard towards others). Scepticism about privacy especially occurs when health care providers do not feel adequately informed or have little technology literacy (Gagnon et al. 2016). The highest acceptance among health care professionals for the use of e- and mHealth interventions can be registered in the areas of prevention and relapse prevention, rehabilitation, self-help and psychoeducation (Surmann et al. 2017).

Teenagers and young adults form the most relevant target group according to practitioners (Hennemann et al. 2016). With regard to therapeutic indication, the acceptance for the use of new technologies in practitioners is the highest among their use in the treatment of depression and anxiety disorders (Liu et al. 2014). Furthermore, age and familiarity with technologies have a significant influence on the attitude and acceptance towards digital health offers (Baumeister et al. 2015; Lin et al. 2018). Practitioners with a higher assurance in handling technologies expect a higher benefit of mHealth apps (Gagnon et al. 2016).

18.6 Acceptance of mHealth Apps in Patients

There is a high acceptance of low-threshold mobile health applications for recording disease course (tracking) among outpatients. Overall 61% would like to receive text messages from their health care providers, 73% would like to access general health care information via the phone, 70% would like to download and use an app to track their mental health condition daily. People over the age of 60 show less interest in using mHealth apps (Torous et al. 2014). In individuals who suffer from depression, anxiety or stress the interest in using mHealth apps was higher when symptoms were present compared to symptom free episodes (Proudfoot et al. 2010). In younger individuals, like university students, the acceptance of the use of apps in health behaviour change is high. Self-reported app use in students is influenced by worries about security, required effort and the immediate effect on mood when using the mHealth app (Dennison et al. 2013). In the general population lack of interest, cost, concern about data collection and data storage are barriers in the adoption of mHealth apps (Krebs and Duncan 2015). In individuals with mental health needs the barriers to uptake and adoption of mHealth apps are doubts about effectiveness (31.4%), finding the right app (27.3%), costs (13.7%), lack of interest (11.1%), concerns about privacy and data security (10.7%), lack of time to use the app (6.6%), lack of space on the personal phone (6%) and usability issues (5%) (Schueller et al. 2018).

The attitude of patients suffering from conditions such as diabetes, depression or pain towards the use of mHealth could be influenced by acceptance facilitation interventions (e.g. a video). Acceptance facilitating interventions subsume any methods that are likely to influence an individual's opinion (e.g. video clips, workshops, advertisements, articles, etc.). In people seeking pain-management the information video changed their attitude towards the use of mHealth significantly. In chronic pain patients this overall effect was not present. Specific subgroups such as younger and female patients as well as patients with a higher actual burden, could be influenced by the video. As a consequence, acceptance-promoting interventions (e.g. videos, brochures, advanced education, journal articles and training) unfold their potential when targeted to the group (Baumeister et al. 2014, 2015; Ebert et al. 2015; Liu et al. 2014).

Half of the individuals who use a mHealth app stop using it after a while. Reasons to stop using mHealth apps are high data entry burden, loss of interest and hidden costs (Krebs and Duncan 2015). Thus, highlighting the importance of passive tracking and the inclusion of persuasive technology to maintain user adherence (Baumeister et al. 2019).

18.7 Risks Associated with mHealth App Use

The CHARISMHA study (Albrecht 2016), a study dealing with the topic of the use of mobile technologies in health-related areas from various perspectives, points to the following risks for mHealth app usage: lack of functionality, dissemination of false information, misdiagnosis, mistreatment and unknown unwanted side effects. An important concern regarding mHealth app use, is the lack of reactivity of algorithms in case of emergency (e.g. self-endangerment or hazards of others). Singh et al. (2016) showed that only 23% of mobile health apps responded adequately to dangerous user input (e.g.: suicidal ideations). This illustrates the enormous need of improvement in terms of responsiveness of mHealth apps in potentially dangerous situations.

Furthermore, it is hard for patients to detect a helpful app and to assess the quality of the content by themselves (Krebs and Duncan 2015). Individuals mainly retrieve information about mHealth apps in social media (45.1%), through personal search (e.g.: in the app stores, via Google or in web forums like Reedit (42.7%) or with the help of a family member or friend (36.9%). Formal sources of information such as health care providers were only used by 24.6% of the individuals (Schueller et al. 2018).

To enable a safe use of mHealth apps, regarding the quality of the therapeutic content, it is necessary to define internationally accepted quality criteria and to distribute this knowledge on a broad scale in an easy understandable way (e.g. quality seals, databases of expert ratings, etc.). In regard to informed health care decisions and patient empowerment, it is essential for patients to have access to standardised ratings of mHealth apps, particularly since the quality of user star ratings is questionable (Terhorst et al. 2018). In regard to safe app use three criteria should be evaluated (1) quality of the therapeutic content, (2) functionality and (3) data safety and protection (Neary and Schueller 2018). While (1) can be reached through open access standardized psychometrically valid expert or user ratings, (2) can be guaranteed through the implementation of a medical device law (e.g. IEC82304 in Europe) and (3) is addressed by data protection regulations such as explicated for example by the European Union.

One current problem is, that many of the above mentioned scientifically examined mHealth apps do not appear in the app stores. In contrast, the majority of available mHealth apps are not tested for effectiveness. To assess the quality of available mHealth apps, our research group evaluated in Germany available mobile health apps for treatment of depression and anxiety disorders as well as for supporting physical activity with a standardized internationally accepted procedure, the mobile applications rating scale (MARS; Stoyanov et al. 2015). To collect the available mobile health apps we developed a web crawler, a program that circumvents the filter settings of the app stores (iTunes, Windows and google play). The ratings of the experts were verified in a further step by an editor and after that published open access on the page www.mhad.science, so that end-users, practitioners and service providers are empowered to take informed health decisions. Overall, the results are eye-opening: the expert rating of all German-speaking depression apps revealed that only 25% of these apps correspond to national guidelines for the treatment of depression. Only 10% of the rated depression apps could be recommended at least based on minimal standards for blended-care or self-help (Terhorst et al. 2018). In terms of mobile health apps that are offered for support and treatment of anxiety disorders in the European app stores, we found similar results. Efficacy studies were present in less than 1% of the rated anxiety apps and none of the depression apps. Anxiety apps developed by universities or non-governmental non-profit organizations (NGO's) showed a higher overall quality. Behaviour therapy alignment as well as the number of offered exercises of the mHealth apps resulted in an elevated quality rating. There was no difference with regard to app quality in relation to the app store and the price of the mHealth app. Analogous to previous studies there was no connection between the star ratings of the app stores (usually given by the app users) and standardized expert ratings (Messner et al., in prep.). One possible explanation of this missing correlation is the lack of knowledge among end users about the applied therapeutic methodology/background as well as the tendency of end-users to judge usability and design instead of effectiveness. In summary, it can be stated that available mHealth apps in Western countries such as Germany with usually high demands regarding patient safety are far below their potential possibilities concerning quality and safety of therapeutic content.

18.8 Standardized Instruments to Assess App Quality

Diverse quality assessment approaches in the evaluation of mHealth apps tend to have reached relative consensus. Current mHealth app quality assessment tools and recommendations tend to focus on a set of criteria such as evidence, information quality, security, engagement and ease of use (often linked to user experience—UX), functionality and visual design. Widely-used tools include the Mobile App Rating Scale (MARS; Stoyanov et al. 2015), the American Psychiatric Association—recommended App Evaluation Model (American Psychiatric Association 2019), and the ASPECTS guide (Torous et al. 2016). Such instruments allow health organizations and information hubs (i.e. Psyberguide.org; KidsHelpline.com.au; Reachout.com; mhad.science) to evaluate and recommend high-quality apps to their clients with increased confidence. Nevertheless, while strongly related to each other, *quality* does not equal *efficacy*. *Effectiveness* and *efficacy* evaluation of mHealth apps remains a time-consuming, complicated and costly process but nevertheless a hot topic in digital health research (Zanaboni et al. 2018). Until international efficacy evaluation and regulation standards are developed, quality ratings may be used for guidance only, but cannot guarantee safety and effectiveness of the intervention.

Another instrument for the evaluation of mHealth programs is Enlight (Baumel et al. 2017), a multidimensional, criteria-based set of scales that assesses the quality of mHealth interventions independently of clinical aim (health related behavior or mental health) or delivery medium (mobile app-based interventions or web-based interventions). It includes two novel concepts that have not been assessed by previous scales: therapeutic persuasiveness and therapeutic alliance. Therapeutic persuasiveness refers to persuasive design, which directly influences users' behavior and a program's therapeutic potential (Webb et al. 2010). Therapeutic alliance is one of the most robust measures for predicting psychotherapy success (Klein et al. 2003) and was included in the quality assessment section, as it has been shown that therapeutic alliances between users and online intervention programs do exist (Bickmore et al. 2005). The instrument consists of a quality assessment section and a checklist section. The quality assessment is comprised of the six core dimensions usability, visual design, user engagement, content, therapeutic persuasiveness, and therapeutic alliance. In contrast, the checklists are based on criteria that do not directly impact the user's experience and include credibility, privacy explanation, basic security, and evidence-based program ranking. The checklist scores are calculated by summing up the scores in each of the categorical items, apart from the evidence-based program ranking, as it is based on a five-point scale.

18.9 Current Legal Situation of mHealth Apps

The so far not adopted regulation of data safety in mHealth apps raises concerns about mHealth app quality and safety of use (Powell et al. 2014). The advances in soft- and hardware development made it possible to collect a vast amount of behavioural and medical data at low cost. This data is very sensitive by nature and an adequate protection is crucial for the safe use of mHealth applications (Kargl et al. 2019; Papageorgiou et al. 2018). The majority of available mobile health apps do not have an understandable privacy policy, so the end users do not know what data will be recorded, how the data will be transferred, where the data will be stored and with whom the data will be shared (Messner et al., in prep.; Terhorst et al. 2018). In general privacy policies lack intelligibility (Papageorgiou et al. 2018). This situation will hopefully change with the implementation of the General Data Protection Regulation of the European Union (GDPR) and the statement of the US Food and Drug administration (FDA). Due to their novelty there is no research on the impact of those regulations on app quality so far.

The new GDPR states a fundamental right of data security for individuals. Every organization has to disclose their practices of data processing, data sharing, and data storage. In case of violation of the GDPR companies can be fined with 4% of annual revenue or up to 20 million€. Users are more seen as owners of their own data, leading to the theory of a basic right to access and delete one's own data as well as to receive an understandable declaration of consent. The informed consent has to be actively accepted per click. In addition, software which is used for administration, maintenance or improvement of the health of individuals succumbs to the "Medical Devices Law" under IEC82304 since May 2017 (International Organisation for Standardization 2016). Thus, increased demands apply on the functionality of mobile health apps. Both legislative changes have the potential to contribute to the improvement of functionality and data security of mHealth apps in the future.

The current situation in the US is more liberal. The US Food and Drug administration (FDA) grades mHealth apps into categories regarding to their potential harm on the user: apps that are medical devices which require regulatory oversight, apps that are medical devices which will not be regulated and apps that are no medical device. Regarding to BinDhim et al. (2015) most mHealth apps will not be classified as regulated medical device and therefore receive no formal regulation, resulting in a need of further quality assessment.

18.10 Summary

Mobile health apps offer great potential with regard to the complementation of routine care, especially in the developing world and for specific subgroups (e.g.: elderly, minorities, rural regions, etc.). The majority of individuals own a smartphone and already use at least one mHealth app. The acceptance of mHealth apps in health care providers is average to low. Concerns regarding the use of apps in health care are mainly about data and user safety as well as effectiveness. There is preliminary evidence for the effectiveness of mHealth app usage. Despite that fact, for the implementation of mHealth apps into routine care social legislation and institutional framework, regulations regarding data safety and an adequate procedure for quality assessment are missing. There are first efforts to increase transparency of app quality through standardized expert and user ratings.

mHealth is a complex domain which requires diverse expertise of health professionals, researchers, designers, developers, legal advisors, and importantly the end-users themselves. It is, therefore, understandable that the development and implementation of best practices and regulations is a slow process. After all, Internet data privacy regulation took decades and a lot of ethical breaches before reaching its current state in 2018. Yet, it is important to adapt and become more agile in our policy-making practices, as the 21st century is yet to expand the new horizons of artificial intelligence and robotics well beyond app use. We should carefully consider our role and contribution towards building the foundations of scientifically, societal and ethically-sound approaches to digital health, to ensure the safe and effective integration of new technologies into healthcare.

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Chapter 19
Using Chatbots to Support Medical and Psychological Treatment Procedures Challenges, Opportunities, Technologies, Reference Architecture

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Abstract The advent of chatbots (also called conversational agents) has been recognized to support various treatment procedures in the medical and psychological fields. Chatbots may be particularly useful before and after medical procedures when patients are at home. For example, while being in the preparation phase of a colonoscopy, a chatbot might answer patient questions more quickly than a doctor. It is more and more discussed whether chatbots may be the first entry point for (urgent) medical questions instead of the consultation of a medical expert, as there exist already well-established algorithms for such situations. For example, if a new medical symptom occurs, a chatbot might serve as the first *expert* to relieve a patient's situation. Such situations are mainly driven by the trend that patients often have to wait very long for appointments with a proper medical expert due to capacity problems of the healthcare system. While the usage of supporting *at home actions* of patients with chatbot technologies is typically welcomed by medical experts, the

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_19

use of this technology to *replace* them in their core competence, namely diagnosis and therapy, is generally seen highly critical. Apart from the domain side, it must be carefully considered what currently available chatbot technologies can do and not do. Moreover, it has also to be considered, how existing technologies can be established in such highly critical (e.g., if a chatbot gets the message of a patient that indicates to commit suicide) and interdisciplinary field, involving ethical questions as well as questions of responsibility and accountability. This work raises aspects that might be the basis for medical as well as technical experts to better collaborate for proper chatbot solutions. Concretely, an architecture is proposed that should serve as a reference for various medical and psychological scenarios. When using suitable technical solutions based on such architectures, we argue that many opportunities emerge, which can mitigate identified challenges significantly.

19.1 Introduction

Although the idea of chatbots, which are also called conversational agents (Wangenheim and Ventouris 2020), is not a recent one (Weizenbaum 1966), the widespread use in healthcare contexts is a recent trend, which is mainly driven by three facts. First, the computational capabilities have been dramatically increased during the last decades. For example, research achievements in the field of artificial intelligence have fanned the use of chatbot technology in the medical context (e.g., Crutzen et al. 2011). Second, the way how present healthcare systems are operated inspire many patients to consider new treatment opportunities. As an example, for many patients with mental health problems, not enough experts are provided by the healthcare systems. In such cases, it is common that patients have to wait for months to get an appointment, which might have crucial drawbacks (Folkins et al. 1980). This setting, in particular, is predestined to utilize chatbot technology as a first entry point to help patients. Third, in many treatment procedures, patients have to accomplish tasks at home. While performing these tasks, patients often feel uncomfortable or they have questions how to accomplish their tasks properly. For example, in the preparation phase of a colonoscopy, patients have often many questions and concerns. However, it is often not possible to quickly talk to a medical expert, what might affect the performance of the colonoscopy. Consequently, medical experts are open for new technologies like chatbots. Although the trend is plausible with respect to the presented reasons, the following three questions emerged in practical projects we are involved in when technical solution shall be implemented:

- If chatbot technology shall be used, can it be offered off-the-shelf?
- Is the technology really already mature for clinical use, especially when off-the-shelf solutions shall be used?
- How much interdisciplinary work is needed to establish chatbot technology for scenarios of different application domains?

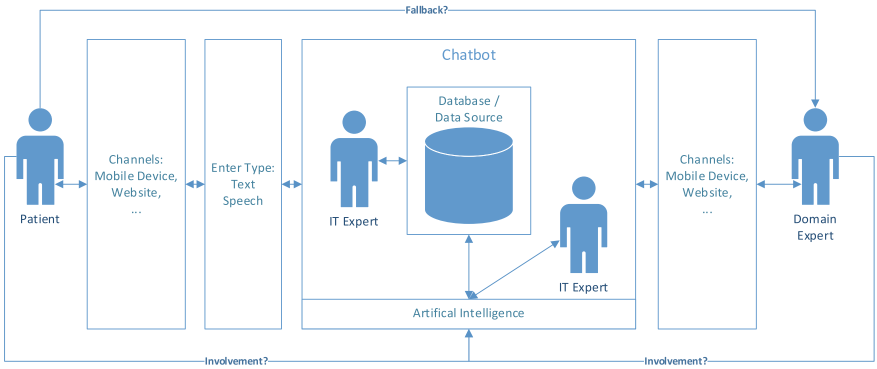

Fig. 19.1 Interplay of decisive aspects of a chatbot system

To answer these questions, we identified an interplay of aspects (i.e., the overall interaction procedure) between patients, domain and IT experts, which must be carefully considered (see Fig. 19.1).

The most important aspects we identified with respect to the overall interaction procedure are as follows:

(1) Which channels shall be provided to a patient to interact with the chatbot? To interact with a mobile device, a website, or both channels has implications for a technical solution. If, for example, a chatbot needs some time for an answer, in the case of a mobile device, a text message can be sent, which, in turn, is more difficult to achieve for a stationary PC setting.
(2) Which ways are allowed for a patient to enter data? There is a huge difference if a patient can only enter textual data compared to speech data or a combination of both. In addition, it must be specified, which languages shall be supported?
(3) Do clinical databases, standard algorithms, or guidelines already exist, on which a chatbot answers can be based on?
(4) What determines if the answer of a chatbot is reliable? Are there any metrics and what reliability is acceptable in such context?
(5) In addition to (4), shall the system support the opportunity that a domain expert is contacted if the chatbot cannot answer in a reliable manner?
(6) How will the domain experts be involved to establish, maintain, and evolve a data source?
(7) Which channels must be provided for domain experts to interact with patients on one hand. On the other hand, which channels are required to interact with the chatbot system?
(8) How can patients be involved to evolve a data source?

Furthermore, the following technical aspects must be dealt with:

(9) Are there any standard technologies or off-the-shelf systems that fit to the requirements of the medical and psychological fields in a flexible way?

(10) What kind of IT experts are needed or should be involved?
(11) What does artificial intelligence in this context mean and can it be measured?
(12) Are there existing (standard) procedures how to establish, maintain, and evolve a data source the chatbot is based on?

Due to space limitations, the work at hand cannot answer all questions in detail. However, two main findings are provided, which can be a basis to tackle the questions. First, we will present the core aspects for establishing a powerful data source the chatbot is working with. In this context, the way it provides the *intelligence* has to be intertwined with the data source in a way that the chatbot is able to learn and improve over time. Despite many challenges that must be tackled, it can be reasonably argued that the opportunities to use chatbots surpass the challenges. However, existing technology is in a premature state that needs fundamental enhancements and considerations. Therefore, as the second finding, we present a reference architecture to realize chatbot systems for medical settings.

The remainder of this work involves six sections organized as follows. In the next section, current research on chatbots is discussed. Then, the sections *Challenges* and *Opportunities* present selected issues, which are particularly crucial to deal with. The section *Reference Architecture* presents a generic architecture, which we figured out as being suitable for various practical settings. Section *Discussion*, in turn, summarizes our findings to establish chatbots in the medical and psychological fields. Finally, section *Summary and Outlook* concludes this chapter and gives an outlook on future work.

19.2 Related Work

The idea of dialogues between humans and machines is as old as evidenced by the development of the Touring-test in 1950. In the sixties and seventies of the last century, the first chatbot implementations for medical and psychological domains have been proposed, e.g., ELIZA (Weizenbaum 1966), which simulates a psychotherapist, or PARRY (Colby 1973), which simulates a paranoid patient. A more recent chatbot implementation, in turn, is ALICE (Wallace 2003), which extends the concept of ELIZA and is based on knowledge of patterns and response templates stored in Artificial Intelligence Markup Language (AIML) files. All of the aforementioned implementations are purely based on *pattern matching* on predefined keywords and templates. Note that this type of chatbot implementations are currently predominant.

More recent chatbots like Jabberwacky (Carpenter 2011) and Cleverbot (Carpenter 2018) are able to learn new responses from the interaction with the user and save them to their database. In general, in recent years, numerous chatbot platforms emerged, which enable developers and businesses to setup their own customized chatbots with minimal efforts. Examples for these platforms are *Pandorabots*, which is based on AIML (Pandorabots 2018), as well as IBM's *Watson Assistant* and Google's *Dialogflow*, which let developers build dialogs through the use of web interfaces by configuring *intents* (the user's anticipated goal) and *entities* (terms or objects that provide context for intents) (Watson Assistant 2018; Dialogflow 2018). However, existing approaches lack holistic considerations how to use the technology in various settings. Furthermore, research on chatbot implementations for the medical and psychological context includes solutions for medical consultations (Comendador et al. 2015; Brixey et al. 2017; Lokman et al. 2009), diagnosis (Divya et al. 2018; Morales-Rodríguez et al. 2010; Mujeeb et al. 2017), primary care (Ni et al. 2017), psychiatric counseling (Oh et al. 2017), or (medical) education (Kazi et al. 2012; Heller et al. 2005). The majority of these implementations are based on AIML or another realization based on pattern matching. An example of a chatbot application that is supposed to help dealing with depression is given by Woebot.[1] The latter applies principles of cognitive behavioral therapy (CBT) to guide patients with their mental health problems.

Recently, the use of chatbots, also called conversational agents, are more and more investigated in studies (e.g., Schachner et al. 2021, Gross 2021). These works conclude with similar findings, especially with respect to the interaction procedure described here. In line with our work, other researchers also take general considerations into account (e.g., Wangenheim and Ventouris 2020), which shows that still many questions have to be answered on a generic level, including that off-the-shelf technology are highly needed.

Technically, suitable generic architectures or other generic technical solutions are less proposed so far (Yan et al. 2016; Reshmi and Balakrishnan 2016), which draw general questions on how to establish chatbot systems in various settings. In addition, guidelines are missing that can be used when starting with new projects. However, more and more approaches show that the need for new findings is high (Cahn 2017). Although platforms like *Pandorabots* exist, configurable off-the-shelf solutions cannot be easily purchased. The development of a suitable data source is the major reason why powerful solutions cannot be realized in a quick and easy manner. Therefore, this work wants to present general considerations on chatbots for medical and psychological treatment procedures.

19.3 Challenges

At first, the technical challenges are summarized to understand the general operation procedure of a chatbot system. Based on this, general considerations on the used knowledge base are presented.

The technical challenges that emerge when designing a chatbot can be categorized into two main areas: *understanding what the user says (or wants)* and *giving an appropriate response*. The first category includes Natural Language Processing (NLP) functionalities like parsing, filtering, normalizing and segmenting the user input, as well as pattern matching. Additionally, advanced chatbots should be context aware,

[1] https://woebothealth.com.

consider the conversation history with the user, and perform a sentiment analysis on the user input. The second category is primarily dependent on a *knowledge base*, which should contain all information that is needed to provide a reasonable response to the user's queries in a specific application context. Best case, this knowledge base is extendable by manual input, integration of existing databases and ontologies as well as machine learning mechanisms in order to continuously improve the response quality (Abdul-Kader and Woods 2015). If the chatbot is supposed to simulate a human conversation partner, another challenge constitutes to make the user believe that he or she is actually communicating with a human being in contrast to a machine; in other words, an ideal chatbot should pass the Turing Test (Turing 2009). To this end, the chatbot might incorporate personalized and contextual responses, varying responses, sensible default responses, canned responses, typing errors and simulation of keystrokes, a model of personal history, and non sequiturs (Abdul-Kader and Woods 2015).

Based on the technical challenges, a decisive step is to understand how the aforementioned knowledge base can be established. In this context, the following questions must be dealt with:

(1) Can existing knowledge bases be used? In addition, are they specifically appropriate for the target setting or do they need adaptions? If adaptions are needed, the question emerges whether adaptions are technically supported?
(2) If existing knowledge bases are planned to be used, who has the knowledge base rights?
(3) How can existing knowledge bases be compared with respect to their quality?
(4) If different knowledge bases exist, do they use the same or a similar vocabulary to configure and maintain data entries? In general, the vocabulary, including the technical configuration and maintenance are crucial aspects for the communication between domain and IT experts.
(5) If no knowledge bases exist or the existing ones are not appropriate, how can a knowledge base be established?

Practical projects have shown that the comprehension in what way such knowledge bases can be created from scratch is crucial. Three general options therefore exist: The first option (I) is to create the knowledge base only manually. This means, IT experts provide features to domain experts to manually enter data to the knowledge base. For example, IBM's *Watson Assistant* and Google's *Dialogflow* provide such functionality. If the knowledge base is created this way, the overall creation takes time. Note that we figured out in practical settings that it is still challenging to establish a reasonable knowledge base from scratch with the IBM's *Watson Assistant*. If existing knowledge bases for diagnostic and therapeutic management or treatment guidelines can be used or bought, then the time period can be decreased. The second option (II) is based on the idea to crawl data of existing data sources, which already provide valuable data. In most cases, such data sources are not intended to be used for chatbots. For example, Internet fora can be used to establish a knowledge base for chatbots. However, such approach is technically challenging. In Dandage 2018, an approach is proposed to evaluate fora threads to help Tinnitus patients in using the fora in question more efficiently. Note that the workflow described in Dandage 2018 should be generally considered to establish knowledge based for chatbots from scratch. Although such approach is technically challenging, three main advantages arise: First, the *wisdom of the crowd* can be exploited. Second, knowledge bases can be established much faster. Third, the workflow to crawl data can be accomplished again and again to improve the overall data quality of the knowledge base over time. The third option (III) is to combine options (I) and (II). Based on the obtained practical experiences, the third option is most promising, particularly, as currently only few knowledge bases exist, which can be easily used off-the-shelf. Therefore, the discussed options to establish a knowledge base are important to consider.

19.4 Opportunities

Chatbots constitute extensive opportunities in the medical and psychological context. They could be used for diagnostic assessment, general counseling, counseling for disease management, counseling before and after diagnostic and therapeutic interventions, disease prevention, treatment and therapy accompaniment, follow-up treatment, (self-) diagnosis, and—ultimately—for offering treatment, e.g., psychotherapy, replacing physicians and psychotherapists to a certain extent. Another opportunity is given by the availability and scalability of chatbots. A chatbot can be available 24 h a day, 7 days a week, at any place with an internet connection, for thousands of concurrent users and can be operated at minimal cost. Providing a comparable availability with trained human experts would be economically unfeasible. The location-independent availability is of particular benefit for immobile users, users in rural areas, or in remote areas with poor medical infrastructure (e.g., workers on oil rigs, ship's crews, war refugees, soldiers etc.). Finally, chatbots would be ideally suited to offer services to people in foreign environments, as they can communicate with the chatbot in their language whereas the use of the medical infrastructure around them is hampered by the language barrier.

19.5 Reference Architecture

We propose a reference architecture for a general chatbot system in the medical and psychological context as shown in Fig. 19.2. Rather than focusing on basic chatbot functionalities like NLP and pattern matching, we wanted to take advantage of existing chatbot services by building a comprehensive system on top of them. On the one hand, this enables a more flexible system regarding overall configuration efforts. On the other hand, a higher precision of responses can be expected. Furthermore, we can take advantage of the evolvements of the integrated services. Further note that we assume that modern chatbot systems are mainly utilized by the use of smart mobile devices. More specifically, the proposed system consists of six major components:

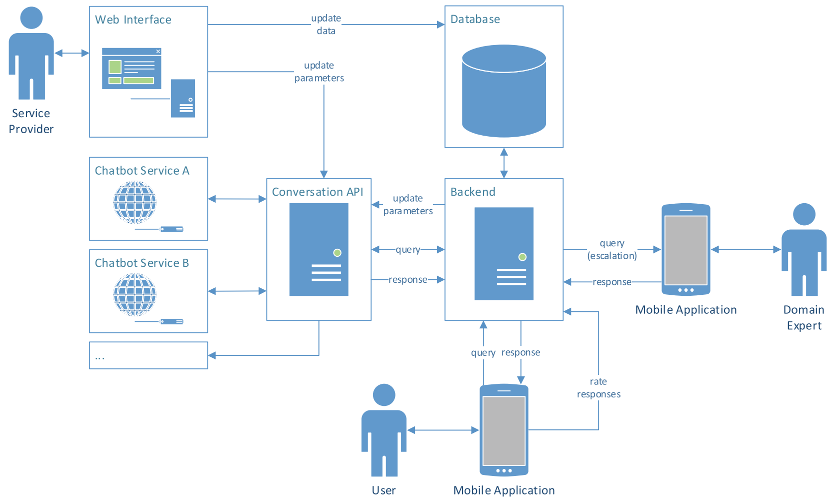

Fig. 19.2 Reference architecture for a chatbot system

a central backend, a *Conversation API*, a database, a web interface for the service provider, and a mobile application for the user as well as the domain expert.

The Conversation API operates as an abstract layer for third-party chatbot services. In our reference implementation, we integrated IBM's *Watson Assistant*[2] and Google's Dialogflow.[3] The API provides a generic interface for intent and example creation as well as chatbot interaction. This way, (a) the different clients do not need to know about the underlying specifics of the third-party chatbot services, (b) replacing a third-party service is facilitated, and (c) the system can use another service as fallback mechanism if one service fails. The database stores user accounts, chat histories of users, messages of domain experts, response ratings, and other meta data. The web interface, in turn, provides access to the database for the service provider. Additionally, it communicates with the Conversation API in order to create and edit chatbot dialog templates. Two customized mobile applications are used for communication between the user and the chatbot as well as the required communication between the user and a domain expert in case of an escalation. The latter reflects the scenario in which the chatbot is not able to provide a reliable response. Such escalation is a powerful way to improve the overall system quality—and therefore its potential acceptance—for patients as well as domain experts. Patients benefit as they get answers to all their questions, while the domain experts learn what requests cannot be answered by the chatbot. This, in turn, enables the chatbot system to evolve by incorporating the response of the domain expert. More technically, a typical interaction between the user and the system might look like as follows:

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[2] https://www.ibm.com/products/watson-assistant.

[3] https://cloud.google.com/dialogflow/docs.

(1) The user enters a text *query* (e.g., a question or problem statement) in the mobile application.
(2) The query is sent to the backend, which, in turn, forwards the query to the Conversation API
(3) The Conversation API forwards the query to one or multiple chatbot services and returns the result to the backend. Then, one of the two following options apply:

   a. The chatbot service is able to respond to the query; the response is therefore sent back to the user (i.e., to the mobile application)
   b. The chatbot service is unable to respond to the query **or** a specific keyword has been detected (e.g., "suicide suspicion") → escalation is required
      i. the query is forwarded to a group of domain experts; a generic response is sent to the user[4]
      ii. a domain expert responds to the query and inputs the chatbot parameters into the system (e.g., intents and examples for IBM Watson)
      iii. the parameters of the chatbot services are updated through the Conversation API in order to be able respond to the query automatically the next time it is detected
      iv. the response is sent back to the user

(4) The mobile application displays the response to the user
(5) (Optional) The user might rate the response. Response ratings are stored in the database and the chatbot service parameters are updated accordingly, either automatically by the system or manually by an expert at a later time. Such feature can again improve the overall system quality and acceptance significantly. One could even integrate a Turing-test -like feature to evaluate whether the chatbot answers are distinguishable from human domain experts' answers.

Three aspects are fundamental when considering the reference architecture. First, a generic interface is used to integrate different chatbot services. This way, the flexibility and quality of the overall system can be improved. Second, an escalation service is used to handle requests that cannot be performed automatically. Third, a rating system is used that enables patients to rate the quality of responses. Although this architecture provides no answer for a proper knowledge base, it provides mechanisms to evolve and maintain existing knowledge bases. In addition, it enables the creation of an independent knowledge base, which can combine existing ones.

[4] e.g. "Your request has been forwarded to one of our experts. We will try to answer as soon as possible.".

19.6 Discussion

This chapter raised questions that emerged in practical projects, which have the goal to design and realize a chatbot system that is able to support medical and psychological treatment procedures. Due to space limitations, not all questions can be answered in detail and, hence, the most important findings are summarized. Currently, only few knowledge bases exist, which can be used off-the-shelf. Therefore, questions to establish such knowledge base must be considered. In addition, the alternatives to build a knowledge base from scratch might be helpful to evaluate a final solution. In this context, five issues are of paramount importance. First, the quality of the knowledge base is key to the quality of the whole system. Since the efficiency and acceptance of the system is mainly dependent on exact responses to the user, much efforts should be spent to reliably build the knowledge base. Second, the development of chatbot systems requires a highly interacting multidisciplinary team, which consist of IT experts, mathematicians, statisticians, domain experts, communication experts/linguists, and software engineers. For example, IT experts must comprehensibly explain the vocabulary of existing systems to domain experts, otherwise misunderstandings may decrease the overall response quality. Third, an escalation service is indispensable to compensate knowledge gaps of the response system to finally improve the used knowledge base. Fourth, a rating system should be also a mandatory service of the system. This way, users' feedbacks can be utilized to improve the system quality. Fifth, at a very early stage, it should be carefully evaluated whether the chatbot system shall accept text input, speech input, or a combination of both. In addition, it should be evaluated which languages must be supported. The presented reference architecture as well as the raised questions may be a valuable starting point to tackle these five important issues to realize a powerful chatbot system that is able to support medical and psychological treatment procedures.

19.7 Summary and Outlook

The chapter provided insights on practical projects with the goal to add beneficial IT support to medical and psychological treatment procedures. The gained insights indicate that the most decisive aspects emerge already at the beginning of any project. More specifically, a set of questions that must be dealt with was presented and, on top of this, the ways how a knowledge base can be established. A reference architecture was conceived to realize a powerful and reliable chatbot system. The way in which the reference architecture is proposed is particularly beneficial with respect to a continuous system evolvement. Overall, although the present challenges surpass the opportunities, in future, it is very likely that chatbot systems will play an increasingly important role to support medical and psychological treatment procedures.

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Chapter 20
Persuasive e-Health Design for Behavior Change

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Abstract At a time, in which people are more and more suffering from lifestyle-related diseases such as cardiovascular diseases, diabetes, or obesity, changing health behavior and preserving a healthy lifestyle are salient factors of any public health effort. Hence, research on predictors and pathways of health behavior change is increasingly important. Following this, new ways of implementing *behavior change interventions* become possible based on internet technologies, allowing for technological approaches to foster behavior change. Such union of media informatics and psychology is denoted as *persuasive design* and refers to all technological intervention components, which help people to take, regularly use and re-take (after relapses into unwanted behavior) interventions. Along this trend, the present chapter introduces (1) theories of health behavior change and summarizes (2) present persuasive design approaches, thereby ending with (3) future directions in the field.

Keywords Persuasive design · Health behavior change · e-health · Lifestyle interventions

20.1 Introduction

A common target of e-health interventions is behavior change towards an increased health-related behavior. This might refer to less alcohol and nicotine consumption,

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_20

increased physical activity, less stressful lifestyle or work-life-balance, safer sexual behavior, medication adherence, or a more positive treatment motivation in general. The latter includes the affinity towards the uptake of indicated, evidence-based health care measures (Baumeister et al. 2008; Renneberg and Hammelstein 2006; Schwarzer 2004). Two research areas have been recently combined to investigate measures to increase the likelihood of behavior change: (1) The field of health psychology-research provides a longstanding expertise on theories and interventions that relates to motivation and more generally health behavior change (Oinas-Kukkonen and Harjumaa 2009; Riley et al. 2011); and (2) the field of (media) informatics, which has developed and examined a multitude of technological features that can foster motivating strategies. These two research fields combined, introduced as *persuasive design*, might enable scholars to address a common and fundamental challenge in the field of evidence-based health care by dealing with the lack of sufficiently motivated patients who cannot be motivated in sufficient numbers in on-site face-to-face settings (Van Ballegooijen et al. 2014; Wangberg et al. 2008). Notably, in the field of information systems, a similar approach is pursued that is called digital nudging (Schneider et al. 2018). This confirms the stakeholder attention for proper and appealing user interfaces, which have been neglected by many digitalization efforts. In the context of Internet- and mobile-based health interventions (IMI), persuasive designs may overcome two of the major challenges in this context: a general low uptake rate and high attrition rates (Ludden et al. 2015; Riley et al. 2011). Along the described challenges, the chapter at hand provides a summary of (1) treatment motivation and behavior change theories, (2) technological approaches to support behavior change, and (3) the integration of both fields to leverage the potential of e-health behavior change interventions.

20.2 Treatment Motivation and Behavior Change

Motivation (latin: motus = motion) refers to a theoretical construct that defines the direction and intensity of a behavior. Motivation is a key predictor (a) towards behavior and (b) maintenance of this behavior, mediated by one's own volition to realize intentions. Volition thereby refers to the means one chooses to realize the intended behavior and the efforts as well as commitments one is willing to invest (Ryan et al. 2011).

Over the last decades, a multitude of health behavior change theories have been established aiming to facilitate the understanding about the reasons why people do (not) live and behave in a beneficial way to their health, especially when considering the present health risks associated with a risky lifestyle or a dysfunctional behavior. Therefore, in the following, the current state of theories on health behavior change is summarized based on Baumeister et al. (2008), providing the basis for developing and implementing technological and digital persuasive solution for facilitating intended behavior.

20.2.1 Health Behavior Change Models

Only a few decades ago, health behavior change knowledge of professionals was rather simple and straightforward. For example, a physician suggests something and the patient adheres to it, such as “smoking can kill you”, with the expectation that this risk indication will actually stop people from smoking. It became quickly obvious that such approaches, associated with a paternalistic communication style that ignores patients’ attitudes and motivations, do not work very well (Schwarzer 2004). Thus, risk perception, as described as a core predictor of behavior in the health belief model (Becker 1947), is still a valid and integral part of most health behavior change models. In addition, two further core predictors of one’s intention have been established in several other models such as the theory of planned behavior (TPB; Ajzen 1985), the social-cognitive theory (SCT; Bandura 2001), the transtheoretical model (TTM; Prochaska and Velicer 1997), the health action process approach (HAPA; Schwarzer 2008), or the technology-related Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al. 2003): Predictor (1) called “self-efficacy” and Predictor (2) called “outcome expectancy”. Note that these constructs, in addition with risk perception (Predictor 3), are the three predictors of intention as defined in the HAPA model (Schwarzer 2008). Furthermore, they can be found in a similar way, but often denoted differently in many other models (see Table 20.1).

Table 20.1 Overlapping constructs of health behavior change models (modified after Renneberg and Hammelstein 2006; Baumeister et al. 2008)

Social-cognitive factors of health behaviour change					
Models	Self-efficacy	Outcome expectancy	Risk perception	Goal setting	Planning
HBM	–	✓[c]	✓	–	–
TPB	✓[a]	✓	–	✓	–
SCT	✓	✓	✓[b]	✓	–
TTM	✓	✓[d]	✓	–	–
UTAUT	✓[e]	✓	–	–	–
HAPA	✓	✓	✓	✓	✓

[a]Perceived behavior control
[b]Implicitly inclosed
[c]Pros minus cons
[d]Decisional balance
[e]Performance expectancy
HAPA Health Action Process Approach; *HBM* Health Believe Model; *TPB* Theory of Planned Behavior; *SCT* Social-Cognitive Theory; *TTM* TransTheoretical Model; *UTAUT* Unified Theory of Acceptance and Use of Technology

20.2.1.1 Predictor 1: Self-efficacy

Self-efficacy refers to the subjective certainty of being capable to master new or challenging situations due to one's own competency (Schwarzer 2004). The construct was introduced in the social-cognitive-theory (SCT) (Bandura 2001) and is viewed as a core predictor of health behavior change (Hardcastle et al. 2015; Schwarzer 2004; Sheeran et al. 2016). In this context, a distinction between generic and context specific self-efficacy has been suggested (Schwarzer 2004). While generic self-efficacy describes a global assessment of one's own confidence of being capable to solve new or challenging tasks, context-specific self-efficacy refers to the expectation of being able to handle a specific situation (e.g., quit smoking, start or maintain physical activity). Current *health behavior change models* further differentiate self-efficacy by regarding the phases of the health behavior change process, starting with *motivation-related self-efficacy* (confidence of being able to achieve the goal), followed by *volition-related self-efficacy* (see below) (Baumeister et al. 2008).

20.2.1.2 Predictor 2: Outcome Expectancy

Different to the construct of self-efficacy, which is used similarly across the different theories, outcome expectancy occurs in most models, but is labeled differently with also varying connotations (Schwarzer 2004; Renneberg and Hammelstein 2006). At least, implicitly, the models define outcome expectancy as a subjective cost–benefit assessment by regarding the expected outcomes of behavior changes. In some of these models, such as the SCT (Bandura 2001), outcome expectancy already includes the construct *social norm*, while others, such as the TPB (Ajzen 1985), and the UTAUT (Venkatesh et al. 2003), define outcome expectancy as a separate predictor. Social norm has thereby been theorized as working through both a social pressure to act (e.g., spouse kindly suggesting to lose weight) and an anticipated reinforcement by meaningful others (e.g., anticipated compliment given to the improved body shape) (Schwarzer 2004). While the latter refers to outcome expectancy (anticipated approval), the former rather can be explained as operant conditioning (negative reinforcement due to the expected discontinuation of the social pressure once the behavior has been changed).

A similar controversy exists regarding the perceived costs of an action. For example, if one thinks of reducing alcohol consumption, a person's expected negative consequence might be abstinence symptoms (=outcome expectancy). Probably, this person would anticipate at the same time that lowering alcohol consumption would be accompanied by substantial emotional stress (=perceived costs of the action). These aspects do not exactly match with the term outcome expectancy and might better be operationalized as action-related expectancies. In the process of an action, such expectancies might refer to cognitions prior (e.g., expected opportunity costs like "when I go jogging twice a week on top of everything else I can't watch my favored TV series anymore"), during ("I will be quite exhausted and fun is something else"), and after the action ("I will be in such a good shape").

20.2.1.3 Predictor 3: Risk Perception

Risk perception as a predictor of motivation (most often operationalized as behavior intention) combines the perceived severity of risks (e.g., diseases following alcohol consumption) and the perceived vulnerability of a person (Baumeister et al. 2008). Risk perception is thereby viewed as a necessary, but not sufficient condition for behavior change. While one might not think of changing anything in case of a lack of risk perception, it is known that when solely communicating the risks associated with a specific behavior such as smoking, alcohol consumption, or risky sexual behavior does not change the respective behavior at large (Ferrer and Klein 2015; Schwarzer 2004). Therefore, the transtheoretical model (Prochaska and Velicer 1997) additionally specifies that for a risk perception leading to intention and actual behavior change, a person must consider the value of a risk negatively for one's own life. Cognitions such as "what do I care if my life is short but lived to the fullest" exemplify the gap between general risk perception and health behavior actions. In other words, humans are always motivated, but maybe not towards the directions health care professionals and caring third parties expect them to be. Thus, next to negatively valued risk perception, one particularly needs to believe that the intended behavior change can be achieved (self-efficacy) and it results in a favorable outcome (=positive outcome expectancy) (Baumeister et al. 2008; Hardcastle et al. 2015; Schwarzer 2004; Sheeran et al. 2016).

20.2.1.4 Intention

Intention is the construct that describes the case that a person decides to change a respective behavior, given a present risk perception and associated psychological strain, sufficient task specific self-efficacy, and outcome expectancy. For a long time, intention has been the postulated core predictor of health behavior change (Knoll et al. 2005). However, as we all experienced failures in regard to New Year's resolutions, the difference between intention and actual behavior change becomes obvious. This is introduced as the *intention-behavior-gap* phenomenon (Conner 2008; Sheeran and Webb 2016; Sutton 2008) and has led current health behavior change models, such as the HAPA (Schwarzer 2004), to introduce a volitional phase, following on one's intention to change a behavior.

20.2.1.5 Volitional Factors of Health Behavior Change

The term volition refers to a process that focuses on the actual realization of a behavioral intention. In the social sciences, volition is seen as a construct that is linked to the philosophical discussion on a free will, which limits the possibility of empirically examining the process behind the *intention-behavior-gap,* with a still ongoing controversial discussion whether volition can be validly assessed (Zhu 2004). However, in the fields of health psychology and motivation research, volition has become an inherent part of modern health behavior change theories (Heckhausen 2007; Renneberg and Hammelstein 2006; Schwarzer 2004).

The HAPA model for example describes a three stepped volitional phase, consisting of a pre-actional, actional and post-actional phase (Schwarzer 2004; Zhang et al. 2019). In the *pre-actional phase,* intentions are transformed into more specific plans about when, where, and how the intended behavior shall take place ("action planning", Sniehotta et al. 2005; "implementation intentions", Gollwitzer 1999). Additionally, one should anticipate possible barriers and challenges to successfully conduct the intended behavior, such as situational temptations (e.g., going in a pub with friends while trying to stay abstinent; "coping planning", Sniehotta et al. 2005). The *actional phase* is characterized by conducting the intended behavior and maintaining it over time (e.g., gym visits twice a week for the next year). Research shows that even freely chosen health behavior actions conducted as part of an experiment already lasted 66 days (median) to become an automatism (Lally et al. 2010). Hence, a core challenge in this actional phase is to protect the intended behavior against alternatives, sometimes tempting motives and aims until the behavior has become part of one's daily life (i.e. habituation kicked in or the behavior runs automatic). Finally, the action is evaluated in the *post-actional phase* and becomes reinforced according to the concept of operant conditioning, which is theorized to impact the reoccurrence of a behavior in dependence of the evaluation and reinforcement.

Again, self-efficacy has been postulated to be a core factor in this volitional phase, with a sub-categorization into "*action self-efficacy*", referring to one's believe of being able to conduct the behavior, "*coping self-efficacy*", referring to ones believe of being able to protect the planned behavior against other plans and temptations, and "*recovery self-efficacy*", referring to the believe in one's own ability to recover from setbacks instead of showing disengagement (Schwarzer 2008).

20.2.1.6 Person- and Personality Characteristics Associated with Health Behavior Change

Inter-individual differences regarding the health behavior baseline as well as differences in the ability of health behavior change are well documented (Kaprio et al. 2002). Most prominently, gender has been examined extensively. For a long period, women were seen as less prone to drinking, smoking, and unhealthy diet, but less physically active compared to men; a view that might have become more complex (McDade-Montez et al. 2007). Regarding age, most risk behaviors decrease with increasing age, while physical activity becomes less likely (McDade-Montez et al. 2007). Most importantly, gender or age are not causal for health behavior, but different bio-psycho-social factors make a specific behavior more likely in one population compared to another. This becomes obvious when looking at the simplification of homosexuality being the core risk factor for HIV in the 1980s. Not homosexuality, but unprotected sexual behavior was always the causal risk factor, which has more frequently been practiced by homosexual men (Hammelstein et al. 2006). Focusing on homosexuality, instead of unprotected sexual intercourse in risk communication and prevention strategies, might therefore be the reason for heterosexual intercourse having become more frequently been associated with HIV than homosexual intercourse in the following years (Hammelstein 2006). Next to socio-demographic variables, personality traits, such as the "big five": o*penness*, conscientiousness, e*xtraversion*, *agreeableness* and *neuroticism* have been suggested as relevant moderators of health behavior and behavior change (Bogg and Roberts 2004; McDade-Montez et al. 2007; Roberts et al. 2005). C*onscientiousness* and *agreeableness* have been associated with positive and *neuroticism* with negative health behavior (McDade-Montez et al. 2007), while results are less conclusive regarding *openness* and *extraversion.* Further personality constructs are frequently discussed, such as *optimism* as way of interpreting information, which might impact ones outcome expectancy (Hammelstein et al. 2006; McDade-Montez et al. 2007; Schwarzer 2004) and *self-directedness* as the ability to regulate and adapt behavior to individually chosen, voluntary goals (Cloninger et al. 1994; Sariyska et al. 2014). Finally, mental disturbances, such as depressive symptoms, are discussed as motivational and volitional barriers towards health behavior change, which one might misinterpret as being non-compliant (Baumeister et al. 2008).

20.3 Persuasive Design: Technological Features to Enhance Health Behavior Change

Digitalization is currently a frequent keyword when it comes to preparing our healthcare services for future challenges, particularly for an aging population with tremendous health care needs in resource-limited healthcare systems (Singh et al. 2016). Several technological solutions for a variety of health conditions, mental disturbances and unfavorable lifestyles have been developed in the last years (Christensen et al. 2009; Day and Sanders 2018; Van Ballegooijen et al. 2014; Wangberg et al. 2008). However, intervention adherence is often one of the core limitations of these otherwise helpful interventions (Baumel et al. 2017; Baumel and Yom-Tov 2018). Persuasive design is one of the constructs that specifically focuses on this human–machine-interaction problem, for which the machine would do the trick if only the human would work like a machine (Kok et al. 2004; Muench and Baumel 2017; Perski et al. 2017). Conflicting motives, a lack of self-efficacy, perceived high costs of the behavior, unfavorable outcomes expectancies a lack of self-efficacy, as well as missing skills and potential temptations in the volitional phase are the key factors, for which persuasive interventions can make a difference (Venkatesh et al. 2003).

Along persuasive design, in the research field of information systems, digital nudging is pursued to investigate appealing and unobtrusive user interfaces. Digital nudges are rooted in behavioural economics aiming at influencing decision-making in digital choice environments (Mirsch et al. 2018). Nudges, in turn, are defined as "intentional and targeted interventions to modify the choice architecture and alter individuals' behavior to a desired direction." (Lembcke et al. 2019, p1). Many research works try to identify psychological effects, which can be then operationalized through nudges. A review in this context can be found, for example, by Mirsch et al. (2017). In the sense of nudges, the goals of persuasive design and digital nudging are similar, someone could say the same. From a global perspective, digital nudging is more rooted at the intersection of information systems, psychology and behavioral economics, while persuasive design at the intersection of media informatics and psychology. Furthermore, persuasive design has a longer history than digital nudging. However, the aforementioned attempt for a differentiation is vague, in-depth looks might reveal other differences, or the two trends may be merged in the future. Nonetheless, the perspective of digital nudging opens room to different conceptualizations around the mechanisms of actions that are involved in behavior change (Domhardt et al. 2021a,b), such as the manipulation of a desired goal's salience in the presence of competing events (for a review see Baumel and Muench 2021).

In the last decade, there has been substantial research efforts in the area of persuasive design. Persuasive technologies are defined as interactive systems, which are intentionally designed to influence their users in order to change their attitude and/or behavior (Fogg 1998). These technologies and their design principles can further be categorized in (a) *primary task support*, (b) *computer–human dialogue support*, (c) *system credibility* and (d) *social support* (Hamari et al. 2014; Oinas-Kukkonen and Harjumaa 2009).

Primary task design principles aim to support the user by achieving his primary goal when using the system (e.g., a successful intervention). The design principles in this category include reduction of complex behavior, guiding the user through the system, tailoring and personalization of content, as well as providing functionalities for self-monitoring (e.g., by visualizing and tracking progress), simulations, or (virtual) rehearsals of behavior. Tikka et al. (2018), for example, presented a gamification approach to promote rehearsals by repeatedly letting the user play a food categorization game in order to improve their game score. However, their study results indicate that rehearsal may not be enough to result in a positive behavior change (Tikka et al. 2018). Anagnostopoulou et al. (2018), as a second example, used personalized persuasive messages in a route planning application in order to motivate users to opt for more environmentally friendly route choices. These context-aware messages implemented self-monitoring (e.g., by providing feedback for past traffic usage) and suggestion (e.g. by suggesting to walk short distances) as persuasive features, and were perceived as useful by the users within a pilot study (Anagnostopoulou et al. 2018). Self-monitoring and mood/behavior-feedback systems have also been implemented frequently in health apps (e.g. Kauer et al. 2012; Montag et al. 2019). Finally, microtargeting approaches are of interest in the context of primary task tailoring and personalisation features. Sending a message fitting to one's own personality for example has been shown to impact on click rates or voting intentions (Zarouali et al. 2020; Matz et al. 2017), approaches that could also be implemented in e-health solutions. However, the component effects of such features in particular, or primary task design principles in general, are still largely unknown.

Computer–human dialogue design principles are supposed to help the users to move towards their goal or target behavior by implementing system feedback (e.g., audio, visual or textual), through direct feedback (i.e., positive and negative reinforcement), rewards (i.e., gamification through credits, points and achievements), reminders and alerts, suggestions and advice, as well as by designing the system in a way that it is appealing to its users and adopts a social role for them (e.g., by incorporating virtual agents). Reddy et al. (2018) conducted a feasibility study in this field of persuasive design technology for a phone-based recommendation system with the goal to change energy usage behavior at home, showing that recommendations may influence participant behavior by increasing their contextual awareness. Another field study showed that an animated character can be used as an imaginative trigger to foster healthy smartphone use (Chow 2018). As a third example, Wais-Zechmann et al. (2018) used personalized reminders and rewards to assist in meeting physical activity goals for patients with COPD (chronic obstructive pulmonary disease). They investigated the perceived persuasiveness within an online study utilizing storyboards, and concluded that these persuasive strategies are rated above average (Wais-Zechmann et al. 2018). While such automatic prompts and reminders are already part of established and well evaluated Internet- and mobile-based interventions (Bendig et al. 2018; Domhardt et al. 2018; Ebert et al. 2018, 2017), the question on when to prompt and remind users in what way and dosage to achieve the best possible behavior change is an open question not yet well understood (Baumeister et al. 2014; Domhardt et al. 2019; Domhardt et al. 2021a; Fry and Neff 2009).

Design principles in the *system credibility* category focus on designing a system that is credible to its users by providing verifiably qualified, truthful, fair and unbiased information, demonstrating experience and competence, having a competent look and feel, and referring to real-world people and respected third-party endorsements. Wais-Zechmann et al. (2018) state that information and suggestions coming from an authority (like physicians or acknowledged institutions) are more persuasive for persons with COPD. Several interventions have already been developed and examined that used such persuasive messages referring to authorities (e.g. doctors and experts) in order to improve participants' intervention expectancy and adherence (e.g. Lin et al. 2017; Baumeister et al. 2021; Sander et al. 2020; Spelt et al. 2018). Whether such authority focused approaches are indeed the best way to optimize system credibility, however, is a question for future studies, which should compare the persuasiveness and effectiveness of authority-based strategies against other possible approaches such as professional look-and-feel strategies, strategies including a buddy avatar, or strategies using labels and certificates of well-respected organizations.

Finally, design features in the *social support* category describe how to design the system in a way that motivates its users by leveraging social influence through functionalities to observe, compare, and learn from other users as well as facilitating interaction, cooperation, competition, and recognition of successfully achieving behavior change goals, e.g., through the sharing of leaderboards or rankings (Hamari et al. 2014; Naslund et al. 2017; Oinas-Kukkonen and Harjumaa 2009; Orji and Moffatt 2018). Examples for this type of features are: interactive tools like messaging and chats with other users, user groups, social media sharing functions, rankings, the possibility to follow and mentoring functions (Mylonopoulou et al. 2018). Wunsch et al. (2015) implemented persuasive strategies in order to encourage biking as low-energy mode of transportation by utilizing recognition (awards based on the number of bike rides), competition (email updates with a leaderboard), cooperation (collective goals), and social comparison (options to compare the number of bike rides with others). They observed an increase in bike sharing for participants receiving the intervention as compared to the control group (Wunsch et al. 2015).

Overall, the field of persuasive design is still in its infancy and the correlation between health-related behavior change and persuasive design enhanced interventions is still unclear. A systematic review concludes that in 75% of the included studies persuasive design was superior to standard design in regard to health behavior change, whereas in 17% of the examined studies positive and negative outcomes have been reported. Finally, 8% of the studies reported no effect of persuasive design on the intended health behavior change (Orji and Moffatt 2018). Hamari et al. (2014) reported in their literature review 52% of positive, 36% of mixed, and 7% of negative outcomes related to persuasive design approaches in health behavior change.

Altogether, when it comes to sustained behavior change in the real world, the different persuasive design components in the system (e.g., feedback, rewards, support) should correspond properly to create a holistic user experience that helps change human behavior in real life. For example, providing people with feedback and rewards without adapting the program based on a user's progress, or without making sure they understand the expectations and relevance of the intervention before they begin, might fail the creation of the holistic experience that is expected to nurture a behavior change. Another aspect that is key in nurturing such an experience is that the quality of persuasive design is important and not only the question of whether a certain checklist of different components was included within the development process. For example, rewarding a person by offering a badge, if it cannot be presented to a group of people this person cares about and who also understand the meaning of the badge, would probably not achieve that same outcome as the intrinsic reward for doing an activity for oneself that can be mirrored through a compassionate statement.

Trying to answer these gaps, recent research introduced the concept of *therapeutic persuasiveness*, which is the way a program is designed as a whole, to encourage users to make positive behavior change in their life. *Therapeutic persuasiveness* includes (1) call to action (e.g., goal setting, prompts), (2) load reduction of activities, (3) real data-driven/adaptive content (monitoring of user state and ongoing adaption of the intervention according to a user's individual progress), (4) ongoing feedback and rewards, and (5) clarity of therapeutic pathway and rational (Baumel et al. 2017). In this sense, *therapeutic persuasiveness* captures the quality of support a user receive from a technological system in his or her own path to achieve the desired goals. Furthermore, therapeutic persuasiveness aims to assess the degree a software is assisting in overcoming emerging difficulties during the behavior change process.

20.4 A Field Moving Forward

Recent technological progress and research trends as well as the prevalence of mobile devices and wearables create promising opportunities in the field of persuasive design. In Table 20.2, the most present persuasive design techniques in the scientific literature are heuristically mapped to the underlying psychological factors that predict health behavior change. While this mapping is based on expert consensus only and should therefore be interpreted as preliminary, it illustrates the broad range of technological approaches for each psychological behavior change dimension. However, common persuasive design techniques address mostly *outcome expectancy* and *self-expectancy*, while *particularly the important predictors of the volitional phase goal setting* and *planning* are less frequently taken into account yet. Therefore, persuasive design approaches that aim to increase health behavior change should include strategies for this volitional phase as well in order to not only facilitating intention, but leading to an actual behavior change.

The acceptance and broad use of mobile devices (such as smartphones, smart watches, etc.) will further provide opportunities to improve the persuasiveness of forthcoming health behavior change approaches. Particularly, opportunities to collect vast amounts of data, combined with new analytical methods such as deep/machine learning, will enable developers to improve the persuasiveness of their systems. These data can be used to (1) gain deeper knowledge about mental states in real-life situations, (2) get insight into the development, maintenance and course of health conditions, (3) evaluate therapeutic processes, (4) give timely or context triggered just-in-time interventions or to suggest tailored interventions (Brunette et al. 2016; Rathner et al. 2018a, b; Rathner et al. 2018a, b). This timely feedback, in combination with the experienced social support, reinforce the adoption and maintenance of healthy behaviors (Naslund et al. 2017). Furthermore, the use of wearable sensors can assist in monitoring health and disease management over extended periods of time, as they need little active user input and therefore compliance (e.g. Ben-Zeev et al. 2015; Lanata et al. 2015; Naslund et al. 2017). To make such use of big data sets, deep machine learning will be one promising computational basis (Bengio et al. 2013; Längkvist et al. 2014; Miotto et al. 2018). It is based on an iterative process of computerized pattern recognition and is therefore well suited to analyze big data exploratively. Theories based on the detected patterns can be subsequently tested in confirmatory study designs and therefore may lead to deeper knowledge.

Overall, the use of persuasive design to foster health behavior change will likely improve the effectiveness of e-health approaches in future. However, this said, we like to end this chapter with a view on ethical aspects related to the use of persuasive design and digital nudging principles (Berdichevsky and Neuenschwander 1999; Meske and Amojo 2020; Cohen 2013), highlighting the need for ethically informed persuasive design research.

Persuasive design builds on the aim of technologically influencing people's attitude and behavior without using coercion or deception (Fogg 2003). Thus, the original

Table 20.2 Persuasive design techniques and proposed[a] corresponding predictors of health behaviour change models

Persuasive design approaches	Techno-logical realization	Psychological dimensions of health behavior change					
		Self-efficacy	Outcome expectancy	Risk perception	Intention-behavior gap	Goal setting	Planning
Self-monitoring and continuous tracking	E.g. EMA[b]	–	–	✓	–	–	–
Visualization	E.g. tracking chart	✓	✓	✓	✓	✓	✓
Tailored content/feedback	E.g. personalized content	✓	✓	✓	✓	✓	✓
Adaptive feedback/content	E.g. chatbot	✓	✓	✓	✓	✓	✓
Reminders/alerts	E.g. push notifications	–	–	✓	✓	–	✓
Suggestions	E.g. lists	–	✓	–	✓	✓	✓
Recognition of achievements	E.g. rewards	✓	✓	–	✓	✓	✓
Sharing and cooperation	E.g. interactive tools	✓	✓	✓	✓	✓	✓
Social comparison	E.g. leaderboards	✓	✓	✓	✓	✓	✓
Empathy	E.g. emotional responsive android	✓	–	–	–	–	–

[a]Mapping based on expert ratings by the authors HB and EMM of the present chapter
[b]Ecological momentary assessment

idea behind persuasive design—and similarly digital nudging—was to technologically support people by clarifying and following their own intrinsic motives and goals in life. Berdichevsky and Neuenschwander (1999) defined eight ethical principles of persuasive design, which shall ensure that the idea behind persuasive design remains intact throughout the development process and usage of persuasive technology. These principles define ethical guidelines for creators of persuasive technology such as not using coercion or deception, transparency regarding creators' motives, reflection about how the technology might be used and ensuring privacy (Berdichevsky and Neuenschwander 1999). Similarly Meske and Amojo (2020) published ethical guidelines for the construction of digital nudges with emphasis on transparency, resistibility (avoiding the nudge is easy and comes without costs) and non-controlling (no incentive/coercion). A further, less commonly mentioned mechanism of ethical control would be to involve users more closely in the development process of persuasive design technology. These are only a few of many ethical and legal aspects that need to be taken into account when creating persuasive health technology in order to exploit its potential in a user and societally beneficial way.

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Chapter 21
Optimizing mHealth Interventions with a Bandit

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Abstract Mobile health (mHealth) interventions can improve health outcomes by intervening in the moment of need or in the right life circumstance. mHealth interventions are now technologically feasible because current off-the-shelf mobile phones can acquire and process data in real time to deliver relevant interventions in the moment. Learning which intervention to provide in the moment, however, is an optimization problem. This book chapter describes one algorithmic approach, a "bandit algorithm," to optimize mHealth interventions. Bandit algorithms are well-studied and are commonly used in online recommendations (e.g., Google's ad placement, or news recommendations). Below, we walk through simulated and real-world examples to demonstrate how bandit algorithms can be used to personalize and contextualize mHealth interventions. We conclude by discussing challenges in developing bandit-based mhealth interventions.

21.1 Introduction

Before mHealth, the standard of care was periodic visits to a clinician's office, interspersed with little to no patient support in between visits. At the clinician's office,

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_21

data is collected to describe the patient's state at that visit time and self-report data about the patient's state prior to the current visit time is collected through an error-prone mechanism of recalling past events. The mHealth model has enabled significant progress in situ data collection between clinic visits; phone sensors can now capture personal data at a millisecond level, and improvement in user interfaces has reduced the burden of self-report information (Kubiak and Smyth 2019). mHealth interventions using persuasive design features are promising approaches for improving patients health (Baumeister et al. 2019; Messner et al. 2019). However providing effective interventions personalized to the patient between patient visits remains challenging.

Two key components of intervening at the right time are personalization and contextualization. Personalization is the process of matching an individual's preferences and lifestyle. e.g., a physical activity intervention can say, "You walked 10 times in the last week near your office. Don't forget to take small walks near your office today." Such personalization can lower barriers to acting on the suggestion (Hochbaum et al. 1952). Contextualization takes personalization one step further by delivering interventions at moments of need or at an opportune moment when the intervention is easy to follow (Fogg 2009). e.g., when a participant reaches the office, a push notification with the earlier walking suggestion can be sent, or, just after a high risk teen reports high stress, a SMS can be sent with ideas to reduce stress.

Contextualization and personalization are complex problems because different people may prefer different interventions and these preferences may vary by context. Fortunately, similar problems have been solved before. When Google places ads or Netflix suggests movies, they adapt their recommendation based on user preferences and characteristics, utilizing bandit algorithms. Here we describe how to repurpose bandit algorithms to personalize and contextualize mHealth interventions. We will start with a simple example, where we personalize a daily list of physical activity suggestions to an individual. We will then extend this simple example to account for contextual factors (e.g., weather). We conclude with a real-world example and discuss future challenges in developing personalized/contextualized interventions with bandit algorithms.

21.2 Background

Bandit algorithms: "Bandit algorithms" are so called because they were first devised for the situation of a gambler playing one-armed bandits (slot machines with a long arm on the side instead of a push button). Each time the gambler picks a slot machine, he/she receives a reward. The bandit problem is to learn how to best sequentially select slot machines so as to maximize total rewards. The fundamental issue of bandit problems is the *exploitation-exploration* tradeoff; here exploitation means re-using highly rewarding slot machines from the past and exploration means trying new or less-used slot machines to gather more information. While exploration may yield less short-term payoff, an exploitation-only approach may miss a highly rewarding slot machine. Researchers have proposed solutions to the bandit's exploit-explore tradeoff across many areas. In particular, once the relevance of bandit algorithms to internet advertising was understood, there was a flurry of work (Bubeck and Cesa-Bianchi 2012). Nowadays, bandit algorithms are theoretically well understood, and their benefits have been empirically demonstrated (Bubeck and Cesa-Bianchi 2012; Chapelle et al. 2012).

An important class of bandit problems is the contextual bandit problem that considers additional contextual information in selecting the slot machine (Woodroofe 1979). Contextual bandit problems provide a natural model for developing mobile health interventions. In this model, the context is the information about the individual's current circumstances, the slot machines correspond to the different intervention options, and the rewards are near-time, proximal, outcomes (Nahum-Shani et al. 2017). In this setup, optimizing mHealth intervention delivery is the act of learning the intervention option that will result in the best proximal outcome in a given circumstance. This is same as solving the contextual bandit problem.

21.3 Optimizing Intervention with a Bandit Algorithm

We will use two simulated examples to explain how bandits can be used to optimize an mHealth intervention for an individual. In Sect. 21.4, we will discuss another real-world mobile application that builds on the ideas introduced in the first two simple examples.

In our first example, the bandit algorithm will be used to select an optimal set of five physical activity suggestions, for an individual, from a set of ten suggestions. A set of five suggestions is optimal if the set leads to the highest level of daily activity for that individual. The second example extends the first by finding a set of five suggestions for each of several contexts. Contextualizing suggestions can be helpful because the same suggestion may be more actionable in certain contexts (e.g., good weather or day of the week).

21.3.1 Personalizing Suggestions for an Individual

Consider a scenario in which Jane's health plan gives her a physical activity tracker and a smartphone app. Jane's health plan has found that the ten activity suggestions from Table 21.1 often work for many less-active people to increase their activity. Note that the order of suggestions in Table 21.1 does not imply any specific ranking. It is unlikely, however, that every individual will be able to follow or prefer to follow all the 10 suggestions equally and there will be inter-personal variability in which suggestions are followed and to what degree. Thus, we set the goal of learning the five suggestions with the highest chance of maximizing Jane's activity. We use the bandit algorithm, which is running as part of Jane's smartphone app, to achieve this

Table 21.1 List of 10 suggestions

1. Walk 30 min
2. Add intervals: walk 5 min, walk very fast for 5 min, repeat 3 times
3. Take the stairs instead of the elevator whenever possible
4. Go for a walk with a friend or your dog
5. Swim a lap, rest 1 min, repeat 10 times
6. Attend a fitness class at your gym
7. Try some of the strength training and bodyweight exercises illustrated by the fitness app on your phone
8. Do yoga
9. Park at the far end of the parking lot to walk farther
10. Do yardwork for at least 10 min

goal. Each morning, the app issues a set of 5 suggestions. The app then monitors Jane's activities throughout the day and uses that information to choose 5 suggestions for the following day.

Formally, we will refer to each set of five activity suggestions as an *intervention option* or *action.* This intervention option or action is the particular choice of the five suggestions. On the morning of day t, the app suggests to Jane the action A_t, where $A_t = [S_{t1}, S_{t2}, S_{t3}, \ldots, S_{t10}]^T$ is a 10×1 vector of binary variables. S_{ti} has a value of 1 if the i-th suggestion from Table 21.1 is shown to Jane on day t, and 0 otherwise. Thus A_t will have 5 entries equal to 1 and 5 entries equal to 0. Further, let Y_t denote the number of active minutes for Jane on day t, which might be called the *proximal outcome* or *reward* of action A_t.

Consider the following linear regression model for the mean of the daily active minutes Y_t on day t in terms of the suggestions:

$$\begin{aligned} E[Y_t|A_t] &= \sum_{i=1}^{10} \beta_i S_{ti} \\ &= \beta^T A_t \end{aligned} \tag{21.1}$$

where the second equality is written more compactly by using vector notation, $\beta = [\beta_1, \beta_2, \ldots, \beta_{10}]^T$. Here $\beta_1, \beta_2, \beta_3, \ldots, \beta_{10}$ respectively represent suggestion $1, 2, 3, \ldots, 10$ s contribution to Jane's number of active minutes. Therefore, Eq. 21.1. has the following simple interpretation: Y_t, the number of daily active minutes, is the sum of the effects of the 5 activity suggestions provided on day t (i.e., suggestions for which $S_{ti} = 1$).

Formally, our goal is to discover the best action $A_t = a^*$ that is, the set of 5 suggestions that makes Jane most active (that results in the highest mean daily active minutes). We can formally write this goal as: given β, determine the action a^* for which

$$\beta^T a^* \geq \beta^T a \tag{21.2}$$

where a is a combination of 5 suggestions from Table 21.1. β is, however, unknown. We can estimate Jane's a^* by running experiments in the following way: at the start of a day t, the app selects action A_t (in other words, it delivers to Jane a combination of 5 suggestions from Table 21.1). The tracker then counts the number of minutes Jane is active on the day (note that this number is the proximal outcome Y_t). If the 5 suggestions are useful, then Jane will be more active that day and Y_t will be high compared to other days with a different set of 5 suggestions. Now, the question is: how to select the 5 suggestions each day? One simple approach is to select 5 suggestions out of 10 with equal probability. But such a uniform selection strategy will select more useful and less useful suggestions equally. A more sophisticated approach is to use the information already available from the past experiments to select future suggestions that will both yield additional information about a^* and give as few less useful suggestions as possible. Note that here we face the same exploit-explore tradeoff faced by the classic bandit setting's gambler—i.e., how to balance exploiting suggestions that seemed useful in the past with exploring less frequently issued suggestions.

An effective approach to delivering less useful suggestions as little as possible is "optimism in the face of uncertainty" epitomized by the Upper Confidence Bound (UCB) technique (Auer et al. 2002; Li et al. 2010). Bandit algorithms based on the UCB have been well studied and possess guarantees of minimizing the number of less useful suggestions. The key intuition behind the UCB idea is the following: First, for each choice of action a_t, a confidence interval is constructed for the linear combination $\beta^T a_t$. Recall this linear combination represents $E[Y_t|A_t = a_t]$, the expected proximal outcome after receiving action, a_t. Then the UCB bandit algorithm selects the action with the highest upper confidence limit. Note that the upper confidence limit for $\beta^T a_t$ can be high for either of two reasons: (1) either $\beta^T a_t$ is large and thus a_t is a good action to make Jane active, or (2) the confidence interval is very wide with a high upper limit, indicating that there is much uncertainty about the value of $\beta^T a_t$. Using the upper confidence limit represents UCB's optimism; UCB is optimistic that actions with high upper confidence limits will be the best actions, even though a larger upper confidence limit can mean more uncertainty. However, if an action with high upper confidence is indeed not the optimal action, then selecting the action will reduce the uncertainty about the effect of this action. This will help UCB realize that the action is indeed not useful.

How does UCB choose an action using the upper confidence interval? By following these two steps. The first step involves using Eq. 21.1 to estimate β assuming homogeneous error variance. We might use ridge regression to estimate β because ridge regression regularizes to avoid overfitting, especially when Jane has just begun to use the app and we have less data (Li et al. 2010; Bishop 2007). In this case the estimator of β, denoted by $\widehat{\beta}_t$, after t days of using the bandit algorithm is:

$$\widehat{\beta}_t = \widehat{\Sigma}_t^{-1}\left(\sum_{u=1}^{t} A_u Y_u\right) \tag{21.3}$$

where $\widehat{\Sigma}_t^{-1} = \sum_{u=1}^{t}\left(A_u A_u^T\right) + I_{10}$ and I_{10} is an 10×10 identity matrix. Equation 21.3 is the standard solution for ridge regression. The second step is to construct an upper confidence limit for $\beta^T a$ for each possible action a; the upper confidence limit on day t for action a is given by $\widehat{\beta}_t^T a + \alpha\sqrt{a^T \widehat{\Sigma}_t^{-1} a}$, where α is an appropriate critical value. Note, since we assumed homogeneous error variance, $\widehat{\Sigma}_t^{-1}$ is proportional to the covariance for $\widehat{\beta}_t$, and $a^T \widehat{\Sigma}_t^{-1} a$ is the covariance of $\beta^T a$. Thus, $\sqrt{a^T \widehat{\Sigma}_t^{-1} a}$ represents standard deviation of $\beta^T a$ and the upper confidence limit of $\beta^T a$ has an interpretable form, which is simply the current estimate, $\widehat{\beta}_t^T a$, plus its standard deviation multiplied up to a constant factor α. Then, to choose the UCB action for day $t + 1$, we calculate the a_{t+1} for which

$$\widehat{\beta}_t^T a_{t+1} + \alpha\sqrt{\alpha_{t+1}^T \widehat{\Sigma}_t^{-1} \alpha_{t+1}} \geq \widehat{\beta}_t^T a + \alpha\sqrt{\alpha^T \widehat{\Sigma}_t^{-1} a} \tag{21.4}$$

for all actions a. i.e., a_{t+1} is selected to maximize the upper confidence limit on the mean of Y_{t+1}. This approach possesses strong guarantees to minimize the number of less useful suggestions (Li et al. 2010; Auer 2002).

Here we summarize how the UCB bandit algorithm works on Jane's smartphone. First there is an "exploration phase" to allow the UCB algorithm to form preliminary estimates of β. This phase lasts for a number of days, say t_0 days, during which each morning the UCB bandit algorithm randomly selects an action, that is, uniformly selects five activity suggestions from the 10, and delivers these suggestions to Jane in the application. Then at the end of day t_0, the UCB bandit uses an incremental calculation to form $\widehat{\beta}_{t_0}$ and $\widehat{\Sigma}_{t_0}$ based on the selected action, Jane's activity minutes, Y_{t_0}, for that day and the prior day's $\widehat{\beta}_{t_0-1}$ and $\widehat{\Sigma}_{t_0-1}$. Next the UCB algorithm calculates the upper confidence limit for each action and selects the action a_{t_0+1} with the highest upper confidence limit. On the next morning, Jane is provided the five suggestions as specified by a_{t_0+1}. The UCB algorithm repeats the process by estimating new $\widehat{\beta}_{t_0+1}$ $\widehat{\Sigma}_{t_0+1}$ and an updated set of 5 suggestions are chosen for the next day and so on.

21.3.1.1 A Simulation Example

In this section, we use a simulated example to demonstrate how a UCB bandit algorithm can personalize suggestions for Jane. We assume the following simple model of how Jane responds to the suggestions: When Jane sees a suggestion, she follows it with probability p or does not follow it with probability $1 - p$. If Jane follows the suggestion, she spends D minutes following it on a particular day. We assume D is random and normally distributed, because Jane may not spend the same amount of time each time she follows the same suggestion. In Table 21.2, we created an artificial example scenario with p and D values for different suggestions. The D values are written as mean ± standard deviation. We also show the expected number

Table 21.2 A simulated scenario for Jane where ***p*** represents the probability of following a suggestion when Jane sees it, and if the suggestion is followed, "Duration" represents the number of daily minutes spent following the suggestion. Finally, ***p*** and "Duration" are used to compute the expected value $pE[D]$, which also represents β values for the suggestion

Suggestions	p	Duration, D (min)	Expected duration $pE[D]$ (min)
1. Walk 30 min	1	15 ± 4	15.0
2. Add intervals: walk 5 min, walk very fast 5 min, repeat 3 times	$\frac{1}{90}$	21 ± 5	0.4
3. Take the stairs instead of the elevator whenever possible	$\frac{5}{7}$	7.5 ± 2	5.2
4. Go with a friend or your dog for a walk	$\frac{6}{7}$	22 ± 10	18.9
5. Swim a lap, rest for 1 min, repeat 10 times	0	–	–
6. Attend a fitness class at your gym	$\frac{1}{14}$	31 ± 5	2.2
7. Try some of the strength training and bodyweight exercises illustrated by the fitness app on your phone	0	–	–
8. Yoga	$\frac{4}{7}$	18 ± 3	10.3
9. Park at the far end of the parking lot to walk further	$\frac{4}{7}$	11 ± 2	6.3
10. Do yardwork for at least 10 min	$\frac{3}{14}$	24 ± 5	5.1

of activity minutes that Jane spends following a suggestion when she sees it. This expected number is $p \times E[D] + (1 - p) \times 0 = pE[D]$. These expected minutes are also β values in Eq. 21.1. Note that β values are unknown in real world setting. We use known β values in a simulated example to show how the UCB algorithm finds the suggestions with higher β values.

With the above setup, we run the simulation in two stages. In the first stage, suggestions are included with equal probability in the five suggestions on each of the first fourteen days. This initial "exploration phase" helps to form an initial estimate of β. In the second stage, we run the UCB bandit algorithm: on each day, we compute $\widehat{\beta}_t$, according to Eq. 21.3, and choose an action using Eq. 21.4. We run these simulation for 56 days, or 8 weeks. We run 200 instances of the simulation to account for randomness in the problem. One source of this randomness comes from the exploration phase, where the app generates non-identical sequences of random suggestions based on when Jane starts using the app. We deal with this randomness by resetting the randomization seed after each simulation run. Another source of randomness comes from the within-person variability of how Jane responds to the suggestions. We create a second stream of random numbers to simulate how Jane responds to the suggestions. The seed of this second stream remains unchanged after each simulation run; we do not reset this seed because, doing so will add the randomness of resetting the seeds to the within-person variability.

Table 21.3 Number of times suggestions are picked by the app within each of the two-week intervals. $\widehat{N}$ denotes the number of days the app selects a suggestion in the time frame mentioned within parenthesis. Note, the number of times a suggestion can be selected during a two-week period is at most 14 (i.e., $\widehat{N} \leq 14$)

Suggestions	1	2	3	4	5	6	7	8	9	10
β	**15.0**	0.4	**5.2**	**18.9**	0.0	2.2	0.0	**10.3**	**6.3**	5.1
$\widehat{N}$ (week 1–2)	**7.1**	7.2	**7.0**	**7.0**	6.8	6.9	6.9	**6.8**	**7.1**	7.1
$\widehat{N}$ (week 3–4)	**12.4**	3.9	**6.3**	**13.4**	2.8	4.5	2.5	**9.6**	**7.8**	6.5
$\widehat{N}$ (week 5–6)	**12.8**	3.5	**6.3**	**13.7**	2.6	4.3	1.7	**10.1**	**8.1**	6.7
$\widehat{N}$ (week 7–8)	**13.1**	3.4	**6.4**	**13.8**	2.4	4.3	1.6	**10.1**	**7.8**	6.8

Table 21.3 shows the results, where we report the mean of the β estimates. At the top, we list the actual β values. We then list in each row how many times a suggestion is issued by UCB over a two week period. We use boldface for the top five suggestions (1st, 3rd, 4th, 8th, 9th in Table 21.1). The simulation shows that after the two-week exploration phase, UCB chooses the top (boldfaced) suggestions more times than the less useful ones. Since a suggestion can be picked only once a day, the top suggestions 1, 2, and 8 from Table 21.3 are picked nearly every day after the exploration phase (11–14 days between week 3–4, 5–6, and 7–8). However, suggestions 3, 9, and 10 all have similar β values. As a result, UCB is often uncertain among them and chooses the 10th suggestion sometimes wrongly, since it is not in the top five suggestions.

21.3.2 *Optimizing Interventions for Different Contexts*

In the earlier section, we discussed an example of personalizing suggestions with the UCB algorithm. Our goal was to demonstrate the inner workings of a bandit algorithm in a simple setting. Here we discuss extending the prior example to a more realistic setting where we tailor suggestion based on users' context. Indeed, context can determine whether, and the degree to which, certain suggestions are actionable. For example, Jane may only be able to act on the yardwork suggestion on the weekend, or she may appreciate and act on the reminder to take her dog for a walk when the weather is good. By adapting suggestions to different contexts, we hope to enhance her activity level. Fortunately, we can contextualize suggestions by re-purposing the bandit technique described already. We briefly describe one way to do so below.

For clarity, we will first consider a very simple context involving only the weather and day of the week. For these two contexts, there are two states (i) weekend or weekday, (ii) good or bad weather, where we consider the whole day as bad weather if only part is. Thus, each day belongs to one of four different context combinations

Table 21.4 Different types of contexts

	Context
1	Bad weather, weekend
2	Bad weather, weekday
3	Good weather, weekend
4	Good weather, weekday

(see Table 21.4). Note this simple characterization of only 4 contexts is to convey the idea of contextualization rather than actually to realistically handle a large number of contexts.

For these four context combinations, the task of contextualizing suggestions boils down to optimizing the suggestions for each of the four. An intuitive approach is to use 4 different bandit algorithms, one for each context combination. Depending on the context on day t, the corresponding bandit would be activated for optimizing suggestions for that context. Recall that an action is a set of five activity suggestions from the 10 in Table 21.1. Each of the four different bandit algorithms uses a model such as Eq. 21.1. but with different βs due to the different contexts. We represent this difference by sub-scripting β as β_k for the k-th ($k = 1, 2, 3, 4$) context. So, the goal is to learn the optimal action a_k^* that maximizes the average number of minutes active for Jane in context k. That is, for $k = 1, 2, 3, 4$ the goal is to learn the action a_k^* which satisfies

$$\beta_k^T a_k^* \geq \beta_k^T a_k$$

Again, one UCB bandit algorithm can be run per context to learn the optimal five suggestions for that context.

Note that using a separate bandit algorithm for each context is not a feasible approach in a real-world setting; there are too many possible contexts. It would take the bandit algorithm many days to obtain good estimates of the β_k parameters. However, we can use a few tricks to handle large number of contexts. First, we may know a priori that some suggestions are equally actionable across different contexts and some suggestions are not at all actionable in certain contexts. If the suggestions are equally actionable across contexts, we can use the same β_k parameter values for these contexts. And if a suggestion is not actionable in a given context we can set its parameter in β_k to zero. Second, we can pool information across people. For example, some suggestions, such as yardwork, are more actionable on weekends for most people. Thus, we don't need to find β_k for each user individually. Pooling information, however, requires a Bayesian approach where for a new user, initially β_k is pooled from prior users and once some data from the user is available, β_k is then adapted to make more user-specific changes. Bayesian approaches to bandit algorithms are beyond the scope of this chapter; but the techniques are along the same lines as UCB (Chapelle and Li 2011).

21.4 A Real-World Example

Earlier, we gave two simple examples of how the UCB bandit algorithm can personalize and contextualize mobile health interventions. Real-world examples, however, are more complicated, with many potential suggestions and many contexts. Below we discuss an mHealth app called MyBehavior that has been deployed multiple times in real world studies (Rabbi et al. 2018; Rabbi et al. 2015). MyBehavior utilizes phone sensor data to design unique suggestions for an individual and subsequently uses a bandit algorithm to find the activity suggestions that maximize chances of daily calorie burns. Like the example in Sect. 21.3, MyBehavior issues the suggestions once each morning. The number of suggestions, however, is higher than in Table 21.1 because the suggestions in MyBehavior closely match an individual's routine behaviors, and routine behaviors are dynamic. In the following, we briefly discuss how MyBehavior uses the bandit algorithm. More information on this can be found in (Rabbi et al. 2017).

21.4.1 MyBehavior: Optimizing Individualized Suggestions to Promote More Physical Activity

The following discussion of MyBehavior first covers how unique suggestions are created for each individual. We then briefly discuss how a bandit algorithm is used to find optimal activity suggestions that have the highest chance of maximizing an individual's daily calorie burn.

The MyBehavior app tracks an individual's physical activity and location every minute. The detected physical activities include walking, running, driving, and being stationary. The app then analyzes the location-tagged activity data to find patterns that are representative of the user's behaviors. Figure 21.1 shows several examples of behaviors found by MyBehavior. Figure 21.1a and b respectively contain places where a user stayed stationary and a location where the user frequently walked. Figure 21.1c shows similar walking behaviors from another user. MyBehavior uses these behavioral patterns to generate suggestions that are unique to each individual. For example, one intervention may suggest an activity goal at specific locations that the user regularly goes to. Such tailoring makes feedback more compelling, since a user's familiarity with the location enhances adherence (Fogg 2009).

Specifically, MyBehavior creates three kinds of uniquely individualized suggestions: (i) for stationary behaviors, MyBehavior pinpoints the locations where the user tends to be stationary and suggests taking small walking breaks every hour in these locations. (ii) for walking behaviors, MyBehavior locates the different places the user usually walks and suggests continuing to walk in those locations (iii) for other behaviors, e.g., participation in yoga class or gym exercises, MyBehavior simply reminds the user to keep up the good work. Figure 21.2 shows several screen shots of the MyBehavior app, where Fig. 21.2a–c are suggestions for three separate users.

Fig. 21.1 Visualization of a user's movements over a week **a** heatmap showing the locations where the user is stationary everyday **b** location traces of frequent walks for the user **c** location traces of frequent walks for another user

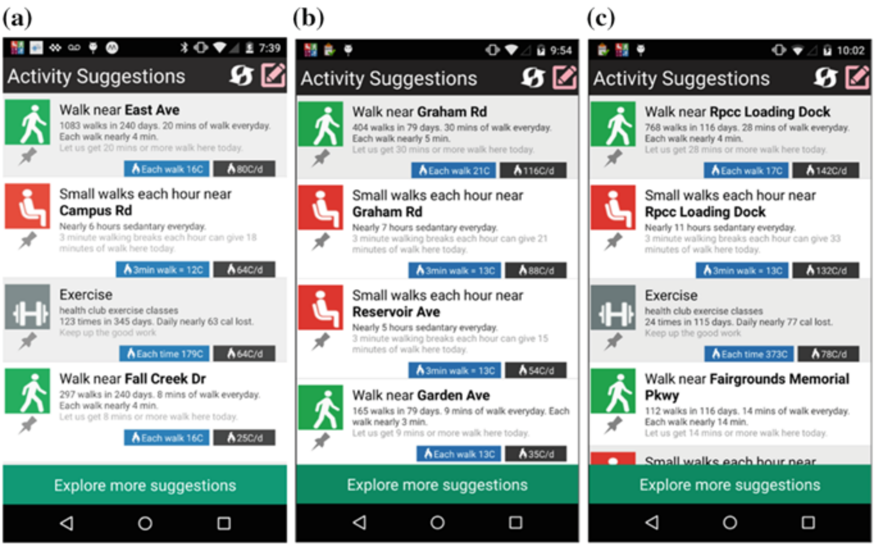

Fig. 21.2 MyBehavior app screenshots for three different users. Figures 21.1 and 21.2 have been reproduced from Rabbi et al. (2015) with appropriate permission from the authors

Since MyBehavior suggestions are tailored to the user, the first suggestion at the top of each screen shot is to walk, but the locations are different. Also, the first and third users receive a gym weight training exercise suggestion that the second user does not.

Now, how does MyBehavior decide which suggestions to give? MyBehavior uses a bandit algorithm like that in Sect. 21.3's first example, where suggestions are issued once a day. But MyBehavior can offer many more suggestions than Table 21.1 contains, depending on the variety of locations in which a user might be sedentary or active, etc. Fortunately, the bandit algorithm can still efficiently adapt to these high numbers of tailored suggestions. Rabbi et al. (2017) details how this optimization works, but the key intuitions are the following: (i) Most human behaviors are highly repetitive and routine and occur in the same locations. Routine behaviors and locations will be detected early and thus included soon in the individual's list of suggestions. (ii) The suggestions relating to routine behaviors and locations are more likely to be followed than suggestions of non-routine behaviors in non-routine locations. Thus, the bandit will learn about the effects of these suggestions more quickly and these suggestions will likely remain effective if the user's routine does not change.

21.5 Discussion

In the last two sections, we discussed several examples of how bandit algorithms can optimize mobile health interventions. The bandit algorithm balances experimenting with different activity suggestions and selecting activity suggestions that currently appear most useful. This balancing act ensures that the algorithm acquires necessary information while maintaining an engaging user experience by providing as few less-useful suggestions as possible. While we showed that bandit algorithms can be useful to personalize and contextualize suggestions, there are additional real-world complexities that pose new challenges for bandit algorithms to address:

Ignoring delayed effects: In bandit algorithms, the optimal action is the action that maximizes the immediate reward (proximal outcome). In other words, bandit algorithms ignore the potential impact of the action on future context and future proximal outcomes. Some actions, however, can have long-term negative effects even if the short-term effect is positive. e.g., delivering an office walking suggestion may increase a user's current activity level, but the user might become bored after repeating the office walk several days, thus future suggestions may be less effective. In these cases, other algorithms that explicitly allow past actions to impact future outcomes (Sutton and Barto 1998) might be used. Precisely, the outcome of these algorithms are $Y_t + V(X_{t+1})$, where $V(X_{t+1})$ is the prediction of the impact of the actions on future proximal outcomes given the context X_{t+1} at the time $t+1$ (a bandit algorithm acts as if $V(X_{t+1}) = 0$). These algorithms tend to learn more slowly than bandit algorithms, since we need additional data to form the prediction $V(X_{t+1})$.

We conjecture that the noisier the data is, the harder it will be to form high quality predictions of $V(X_{t+1})$ and thus as a result, bandit algorithms may still be preferable.

Non-stationarity: Most bandit algorithms assume "stationary" settings; i.e., the responsivity of a user in a given context to an action does not change with time. This assumption can be violated in real-word settings; in MyBehavior, for example, we observed that many suggestions become ineffective when people switched job and moved from one location to another. Such changes over time are often referred to as "non-stationarity." Other types of non-stationarity can be caused by life events such as a significant other's illness or aging. Bandit algorithms are typically slow to adapt to non-stationarity. Speeding up this process is a critical direction for future bandit research.

Dealing with less data: In real world applications, where the number of contexts and actions are many, bandit algorithms will need a lot of burdensome experimentation to find the optimal action for a given context. One way around this is to use a "warm start." A warm start set of decision rules that link the context to the action can be constructed using data from micro-randomized trials (Klasnja et al. 2015) involving similar individuals. Recently Lei et al. (2014) developed a bandit algorithm that can employ a warm start. However, we still need to test whether, and in which settings, warm starts will sufficiently speed up learning.

Adverse effects: Since mHealth interventions are generally behavioral, the risk of personal harm is often minimal. Nonetheless, there could be potential iatrogenic effect because phones cannot capture every piece of contextual information and bandit algorithms ignore the long-term effects of interventions. Since bandit algorithms don't take interventions' long-term effects into account, the algorithm may notify or otherwise deliver interventions too much and thus cause annoyance and reduce app engagement. Future work needs to investigate how to account for such long-term adverse effects. Furthermore, current phone sensors cannot automatically capture critical contextual information such as a user's health risks, preferences, barriers, emotional states, etc. Incomplete information may cause the algorithm to provide less appealing (e.g., not suggesting an activity that a user likes but didn't do often in the past) and inappropriate suggestions (e.g., asking someone who is injured to walk). Providing human control over the suggestion generation process can mitigate these problems; e.g., a user can delete inappropriate suggestions and prioritize the suggestions that are more appealing (Rabbi et al. 2015).

Acknowledgements This work has been supported by NIDA P50 DA039838 (PI Linda Collins), NIAAA R01 AA023187 (PI S. Murphy), NHLBI/NIA R01 HL125440 (PI: PK), NIBIB U54EB020404 (PI: SK). A. Tewari acknowledges the support of a Sloan Research Fellowship and an NSF CAREER grant IIS-1452099.

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Chapter 22
Parkinsonism and Digital Measurement

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Abstract Parkinson's disease and "Parkinson's plus" syndromes such as Progressive Supranuclear Palsy are a group of neurodegenerative conditions characterised by changes in movement amongst other abnormalities. Motor symptoms, such as tremors, gait changes, and bradykinesia, emerge due to loss of neurons in the basal ganglia of the deep brain. No simple, specific, quantifiable, and readily available test exists to aid the diagnosis of these conditions. Clinical examination remains the gold standard, yet this relies on subjective assessments of symptom severity. Invasive tests including analysis of blood and cerebrospinal fluid have been disappointing. However, thanks to novel technology we now have the ability to quantify motor disturbances accurately, from finger movements and tremors to saccadic eye movements and gait. Improvements in computational power and battery life have enabled sensors to become smaller whilst ever more precise. Motor biomarkers are non-invasive and therefore well suited to longitudinal, remote, monitoring. For these reasons, over the last decade, there has been a shift from focusing solely on invasive biomarkers to a greater emphasis on non-invasive motor markers. In this chapter we introduce two examples of neurological conditions which are the subject of active motor biomarker research and describe some of the digital phenotyping methods being applied to these disorders. In addition, we outline future developments including remote testing and contactless testing. Due to the COVID-19 pandemic and resultant isolation and physical distancing measures, the shift towards the homes of participants as the location for motor quantification experiments is accelerating. We discuss the benefits and considerations of this paradigm shift through the lens of clinical research generally and Parkinson's and Progressive Supranuclear Palsy research specifically.

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*,
Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_22

22.1 Clinical Biomarkers

Medicine has been searching for biomarkers—clinical correlates that accurately reflect disease presence—for millennia. The Egyptian Edwin Smith Papyrus, dating 1600BC, is the first medical treatise to formally describe diagnostic biomarkers (Moore 2011). Ancient texts describe intracranial pulsations and wrist pulses were correctly thought to correlate with severity of disease. Since then, thanks to an exponential increase in technology and accuracy, each hospital visit now involves testing for a range of biomarkers—from less invasive blood tests and imaging to intraoperative biopsies.

Diseases of the brain and nervous system have been harder to investigate—in part due to the blood–brain barrier. This physical defensive mechanism isolates our central nervous system from pathogens circulating the blood stream (Jurado and Walker 1990). Consequently, blood tests are far less useful in characterizing neurological disease—or more generally brain function—compared with organs such as the kidney and liver (Daneman and Prat 2015). Lumbar punctures, commonly referred to as spinal taps, allow clinicians to sample fluid surrounding (and hence, interacting with) the brain and spinal cord to test for brain-based biomarkers (Kansal and Irwin 2015). However this process is painful, requires specialist expertise and can only be done safely in a hospital setting. Moreover, the results obtained from studies investigating potential chemical biomarkers in both blood and CSF in neurodegenerative conditions have been disappointing. Until recently this meant that the science of detecting common neurodegenerative diseases such as Alzheimer's, Multiple Sclerosis, and PD is far less precise in comparison to diseases affecting other organs.

22.2 Parkinson's Disease

In 1817, James Parkinson described six patients presenting paralysis agitans—a 'shaking palsy', featuring stiffness of the limbs, slowness of movement, and tremor (Parkinson 1969). This seminal case series describing the now eponymously named Parkinson's disease (PD) postulated that the presenting symptoms were caused by an *"irremediable diminution of the nervous influence"*, and concluded that no treatment alleviated symptoms nor affected life expectancy. PD is now known to be a neurodegenerative condition, and, while we do have a range of symptomatic treatments, the phrase 'irremediable diminution' remains appropriate because we still have no treatment that will slow the degenerative process down.

The principal motor symptoms of PD are caused by the loss of dopaminergic cells in the midbrain substantia nigra pars compacta (SNc), and their projections to the striatum, part of an area of the deep brain called the basal ganglia (Galvan and Wichmann 2008). Studies estimate approximately 50% of dopaminergic neurons degenerate before motor (movement) symptoms appear in patients. In addition to tremors, rigidity, and bradykinesia (slow movements), PD often causes changes in one's pattern of walking (gait), partly due to the loss of dopamine and partly due to degeneration of another population of neurons in the brainstem that produce a different neurotransmitter, acetylcholine (Armstrong and Okun 2020).

Currently the most widely accepted way of measuring the severity of PD is using a clinical rating scale, the latest version of which is the Movement Disorders Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS) (Galvan and Wichmann 2008). Scales such as these are subjective, being influenced by the raters' judgements, and thus create substantial inter-rater variation and resultant noise (Chaudhuri et al. 2019).

However, thanks to the advent of sophisticated measuring devices, small changes in motor function can be objectively measured. The aim of motor biomarker research is to accurately map quantifiable data with disease presence, trajectory, and effectiveness of treatments.

22.3 Progressive Supranuclear Palsy

Progressive Supranuclear Palsy (PSP) is a neurodegenerative disorder characterised by a rapidly progressive loss of balance, postural instability, bradykinesia, supranuclear gaze palsy, and in some cases severe cognitive deficits (FitzGerald et al. 2018). The prevailing pathological hypothesis attributes these symptoms to abnormal tau protein deposition in specific parts of the brain: the basal ganglia (subthalamic nucleus (STN), substantia nigra (SN), globus pallidus (GP)), dopaminergic oculomotor nuclei in the brain stem, and the cerebral cortex (frontal lobes and limbic system) (Boeve 2012).

PSP often bears a strong resemblance to PD early in its course so distinguishing between the two is a challenging task. Due to this overlap, the treatment of PSP patients often starts with PD drugs and the disease is only correctly diagnosed after a failure of medication targeting the dopaminergic system. Pharmaceutical options used in the treatment of PD offer very little efficacy, and tau-reducing agents have yielded similarly poor results (Shoeibi et al. 2019).

Due to the complexity in diagnosing PSP, there have been efforts to develop an objective scale to monitor clinical deficits in patients with PSP across its broad phenotypes, such as the Progressive Supranuclear Palsy Clinical Deficits Scale which have proven very useful (Piot et al. 2020).

An objective test would potentially allow PSP to be identified at the earlier stages. However, current attempts at developing such tests have been largely unsuccessful. One example, MRI-based brainstem morphometry, has at best achieved a positive predictive value (PPV) of just under 60%. Cerebrospinal fluid studies, using lumbar punctures, have revealed borderline or no significant differences between PSP and PD groups (Lang 2014).

Another approach would be to accurately quantify the cognitive and neurophysiological symptoms of PSP. Tests can measure the typical deficits in executive function (cognitive inflexibility, planning deficits, impulsivity), motivation, and language (impaired verbal fluency). In addition to a battery of cognitive tasks, using wearable devices and video recording technology can add reliability and reproducibility to previously highly subjective measures of bradykinesia, balance, and oculomotor dysfunction. We will be describing some of our ongoing work on this later in this chapter.

As noted, both PD and PSP cause a variety of motor symptoms including changes in gait, a slowing of movement, subtle changes in eye movements and a characteristic tremor. Though each patient has variable symptoms, the severity of symptoms present correlate with the severity of disease. By accurately measuring these symptoms, using portable digital technology—over periods of time—neuroscientists hope to find objective markers for PD and PSP. In the following sections of this chapter, these aforementioned types of movements will be discussed through the lens of disease pathophysiology and benefits of digital measurement.

22.4 Gait

Gait disturbance is one of the most prominent features of PD. PD disrupts the cortico-basal ganglia-thalamo-cortical loop which is important in motor, oculomotor and higher cognitive function (Caligiore et al. 2016). The motor circuit involves the putamen receiving input from the supplementary motor area (SMA), motor cortex, and somatosensory cortex, then passing it on the internal globus pallidus and substantia nigra pars reticulata (SNpr) before closing the loop to the cortex.

PD gait is characteristically slow (bradykinetic), with small steps and reduced foot lifting (commonly described as shuffling), postural instability, and reduced arm swing. A stooped posture, and difficulty initiating movement are often observed (Murray et al. 1978; Morris et al. 2010; Hausdorff et al. 1998) PD patients also exhibit the heel-to-toe characteristic, where the entire foot touches the ground at the same time as opposed to the heel touching the ground first as in normal walking (Hughes et al. 1990). In advanced cases, patients often experience freezing-of-gait (FoG) where they are unable to lift their feet off the ground. Gait instability can increase the tendency for patients to fall, leading to injuries.

Potential PD-specific gait and balance metrics can be grouped into three categories based on neural control systems: gait, postural sway, and postural transition (Horak and Mancini 2013). Arm swing, trunk motion during gait, postural sway, anticipatory postural adjustments (APAs) during postural transitions, and gait variabilities have been listed as the most promising measures in PD assessment.

Gait is a complex sensorimotor activity which involves spatial–temporal coordination of the legs, trunk and arms, as well as control of dynamic equilibrium, all of which are affected by PD (Winter 2009; Schoneburg et al. 2013). Complex sensorimotor control loops are involved in maintaining balance, which can be measured through postural sway (Maurer et al. 2006). Postural sway has also been found to be a more sensitive alternative to clinical rating scales in measuring changes from a physical therapy postural agility program (King et al. 2013).

Postural transition is an interesting marker as bradykinetic PD patients are found to be much slower in adapting to changes in postural perturbations (Chong et al. 1999). This suggests the existence of a BG-specific set-switch control mechanism, which may correlate with our eyes ability to move and unconsciously shift attention between tasks. Step initiation is also important as PD patients are known to be slow at initiating new movements. Postural transition can also be used to distinguish fallers from non-fallers (King et al. 2012; Weiss et al. 2010; Greene et al. 2012).

Previous studies have evaluated Parkinsonian gait and the effects of therapy using force plates, cell phones, and single sensors placed at different locations on the body. However, these instruments are limited to only capturing certain aspects of gait and use gross measurements to describe the entire body's gait characteristic. In the Oxford QUantification In Parkinsonism (OXQUIP) study, we used a wearable sensor network (see Fig. 22.1) that tracks gait parameters from six sensors placed on the trunk and extremities (2 wrists, 2 feet, 1 sternum and 1 lumbar) to capture a fuller clinical picture of the Parkinsonian gait and treatment effect. Each sensor contains triaxial accelerometers, gyroscopes, and magnetometers, for a total of 54 data channels yielding 10 Mb of data per minute at a sampling rate of 100 Hz. These sensors have wide applications not only in the clinical setting but also in home-monitoring of patients as they are easily applied with a fully automated data collection process.

From the clinical viewpoint, both medication and Deep Brain Stimulation (DBS) improve PD symptoms, however, mobile sensors have been able to identify and quantify differences in their effects. In particular, levodopa medication and DBS at the STN seem to have opposing effects on sway dispersion, sway, cadence, and APA (Rocchi et al. 2002, 2012; Nantel et al. 2012; Johnsen et al. 2009). Using the APDM sensors in the OXQUIP protocol (see Fig. 22.2), our group has identified a different effect of medication and DBS on gait rhythmicity, in addition to the beneficial effect on classic gait parameters such as stride length, gait speed, foot strike angle and toe-off angle (Su et al. 2020). STN-DBS had a significant normalising effect on the lower limb rhythmicity parameters, while levodopa medication had no such effect. Gait variability measurement has been made possible with mobile sensing devices collecting thousands of data points during the short task duration, replacing force maps and video-analysis systems previously used in gait laboratories.

PSP, as explained earlier, is a condition that can look similar to PD for several years. The prognosis is very different, and it is important to be able to give people an accurate diagnosis. It is also critical when developing new treatments. Using data from participants (both PD and PSP) in the OXQUIP trial, and an automated classification machine learning algorithm, differences in gait, sway and a timed up-and-go task were analysed (Vos et al. 2020). We found that a wearable 6-sensor array coupled with machine learning methods accurately distinguished PSP from PD with 86% sensitivity and 90% specificity (Vos et al. 2020). The array complexity (i.e., how many sensors are attached to different body parts) is an important strategic choice: more complex arrays are likely to improve data quality but at the expense of potentially lowering patient compliance. Complexity is likely to depend on context. For instance, if there is a critical need for accurate diagnosis then a high specificity is

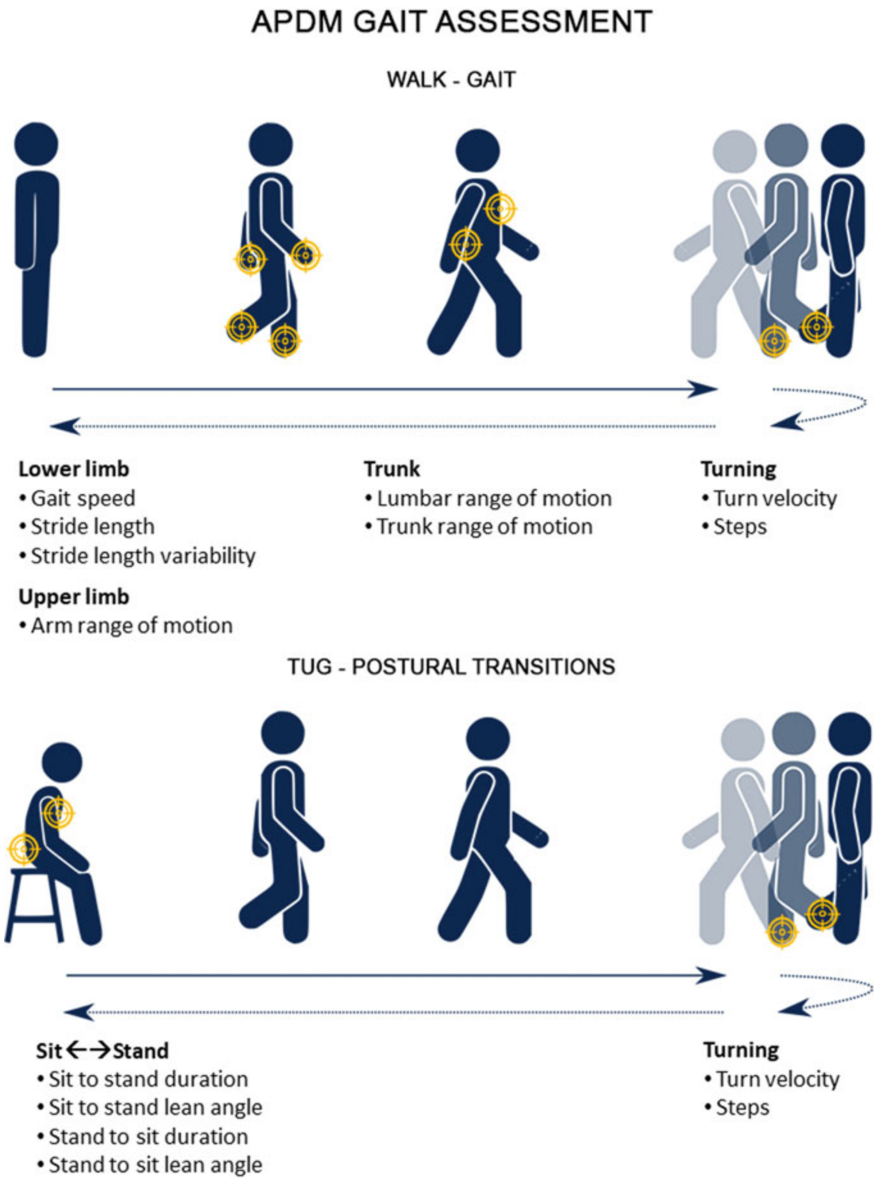

Fig. 22.1 Gait assessment using kinematics analysis (APDM Inc system) for the OxQUIP—Oxford Quantification in Parkinsonism study

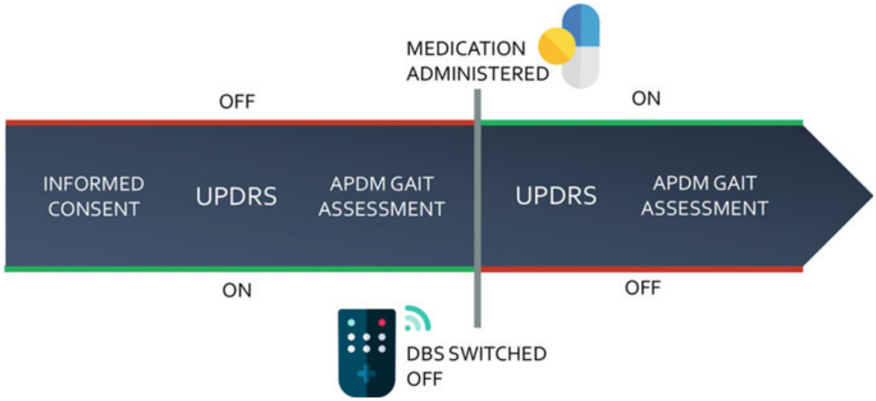

Fig. 22.2 Protocol used for the Parkinson's patients who have undergone deep brain stimulation

needed and a more complete array is advantageous. If, however, diagnosis is secure and disease tracking is the point of interest then a simpler system (for instance 3 sensors) may suffice. Future studies will concentrate on longitudinal differences in PD and PSP enabling both disease progression and intervention effectiveness to be quantified.

22.5 Tremor

Tremor is a characteristic symptom of PD (Hallett 2012). Rhythmic, involuntary, oscillatory movements occur due to alternating contraction of antagonist muscle groups. The upper limbs are most commonly affected but tremor can occur throughout the body. Tremor can reduce the quality of life of patients by interfering with simple tasks including drinking from a cup without spilling, but also eating, dressing, and writing, and through the embarrassment that it can cause (Heusinkveld et al. 2018).

Tremors can be divided into those occurring at rest and those occurring during action (Puschmann and Wszolek 2011). Rest tremors can often be seen in the hands when they are placed upon the lap or when the arm is hanging by the side. This type of tremor is the most common in PD. A 4–6 Hz frequency "pill-rolling" action is commonly noted which ceases upon initiation of movement. Action tremors occur during movement and can be subdivided further into postural, kinetic, intention, task-specific and isometric groups. PD studies mostly focus on rest, kinetic and postural tremors.

Tremor pathophysiology is still incompletely understood but researchers hypothesize multiple brain networks are involved, manifesting as these subtly different types of tremor (Thenganatt and Louis 2012). Functional neuroimaging has highlighted the importance of the basal ganglia and cerebellum in PD induced tremors (Niethammer et al. 2012). Post-mortem analysis indicated reduced grey matter density in the cerebellar right quadrangular lobe (Benninger et al. 2009). Deep brain stimulation has been shown to be particularly effective at reducing the magnitude of tremors. Specific areas of the thalamus, such as the ventral intermediate nucleus (VIM) which receives input from the cerebellum via the dentatothalamic tract are established targets for stimulation (Akram et al. 2018).

The amplitude and frequency of tremor can be accurately quantified using accelerometers or inertial measurement units. This enables researchers to objectively evaluate this aspect of PD, and potentially use it to track disease progression precisely. Subtle differences in types of tremors could be differentiated, using unsupervised learning techniques, yielding diagnostically useful information.

22.6 Eye Movements

Oculomotor control circuits pass through many of the same parts of the brain that are affected by PD pathology. It is therefore not surprising that many studies have demonstrated eye movement abnormalities in PD. This has led to measurement of oculomotor function being proposed as a potential diagnostic biomarker (Antoniades et al. 2015).

Measurement of eye movements is quick, easy and non-invasive. Participants are typically instructed to perform specific tasks, for instance to follow a red dot on a wall or screen, while a camera or a microsensor (infrared camera) tracks the motion of a specific part of the eye. For example, a video camera may be used to record eye movements and software can then detect the pupil within the image and follow its movement. An alternative to video recording is the head-mounted infra-red oculometer: worn like spectacles, the device incorporates three lasers projecting a central red fixation dot on the wall in front of the participant, with two peripheral targets at $\pm 10°$, as well as infrared sensors in the nose bridge that track the position of the edge of the cornea.

A wide range of oculomotor tasks have been described, featuring various levels of neural processing complexity. A pro-saccade task, where participants are instructed to move their eyes to the location of a newly appearing target, requires only circuitry within the basal ganglia. In the anti-saccade task—looking away from a target—participants need first to inhibit the urge to look towards the target, and then consciously generate an eye movement in the opposite direction, both requiring inputs from the dorsolateral prefrontal cortex (Munoz and Everling 2004).

Drugs used to alleviate PD symptoms can also influence eye movement parameters. PD prolongs prosaccade latency, and perhaps surprisingly levodopa has been shown to increase it further. Anti-saccadic latency, however, appears to be largely unaffected by medication, and may therefore be a better measure of disease state (Lu et al. 2019). Deep Brain Stimulation (DBS) can also produce oculomotor changes (Shaikh et al. 2018). DBS of STN or the globus pallidus interna (GPi) has an opposite effect to levodopa: it reduces the pro-saccadic latency, with DBS-GPi also improving the anti-saccadic error rate (Straube et al. 1998). Interestingly, this is not achieved by ablation surgery, despite similar global symptomatic improvement.

PSP causes a distinct pattern of oculomotor pathology, with cardinal features of slowness and hypometria of vertical saccades and vergence problems. These may be detectable on clinical examination but more subtle abnormalities may require formal measurements such as saccadometry or video eye tracking (Antoniades et al. 2013).

Visual search is an example of how PSP eye impairment can be demonstrated using a predominantly cognitive task. Deficits in stable fixation and vertical eye movements are an important part of an effective executive function and thus PSP often features severe delays or inefficiencies in finding objects or recognising spatial changes (Smith and Archibald 2020).

The control of eye movements provides a unique opportunity to understand how the brain works. Over the last three to four decades eye movements have increasingly been applied as an experimental tool to gain insight into a range of disorders (Leigh and Zee 2015). As discussed earlier, medication can significantly prolong a reflexive eye movement such as in a prosaccadic task without any other changes in any of the other saccadic parameters. Antisaccadic latency is particularly interesting because it shows a large disease effect with no medication effect (Lu et al. 2019). Such findings pave the way to the possibility of using eye movement recordings as markers of disease, treatment effectiveness and in aiding in differential diagnosis.

22.7 Finger Tapping

One type of finger tapping task—tapping the index finger on the thumb of the same hand—is part of the standard clinical assessment of PD. Abnormalities include slowness (low tapping rate), reduced amplitude, or irregularity.

A wide variety of other tapping tasks have been described. Some involve tapping repetitively in one place on a surface, while others alternate back and forth between two locations. Tapping may be detected by accelerometer on the fingers or wrist (Kinesia), by activation of a switch, contact with a touch pad, or the screen of a smart device (Antoniades et al. 2012; Lee et al. 2016; Stamatakis et al. 2013). All of these methods provide the ability to estimate not only simple parameters such as tapping rate and intertap intervals, but also features of tapping rhythm and its variability. Complex algorithms have been developed to model the pattern of short sequences of taps (Roalf et al. 2018; Lainscsek et al. 2012).

Finger tapping in PD is influenced by symptomatic treatment. Both antiparkinsonian medication and bilateral STN DBS significantly improved repetitive alternating finger-tapping rates (Brodsky et al. 2010; Taylor Tavares et al. 2005).

One recent study published in 2020 trained a neural network to measure finger tapping from smartphone videos (Williams et al. 2020). The deep convolutional neural network, DeepLabCut, consisted of a version of ResNets (a network pre-trained on ImageNet, a large repository of objects, for accurate object recognition) (Mathis et al. 2018). Thanks to the pretrained component, DeepLabCut could take advantage of a component of deep learning called transfer learning. Transfer learning allows a model, already trained for a previous task, to be repurposed for a new task without further training. This allowed DeepLabCut to recognise and track multiple body parts without the need for large amounts of new data. Six key anatomical landmarks on a hand were identified ("*thumb tip; index finger tip; thumb metacarpophalangeal (MCP) joint; index finger MCP joint; middle finger tip; dorsal wrist/proximal dorsal hand*"). 137 videos of finger tapping, labelled with each of these six locations was the sole novel data used to train DeepLabCut for this study.

The study from Williams et al. (2020) measured speed, amplitude and rhythm of finger tapping tasks. Tasks were filmed on smartphones and video footage was fed into DeepLabCut. Resultant measurements corresponded to the participants' clinical UPDRS scores as assessed by 22 consultant neurologists in the United Kingdom. The authors identified another advantage to this remote, accurate, measurement of this approach: the contactless component. No wearable sensor was needed. The DeepLabCut study even removed the need for computers—and in an increasingly smartphone reliant society, it would be sensible to assume all participants would have access to such universal technology.

22.8 Future Developments

COVID-19 and resultant safety measures have had a big impact on clinic-based medical research. Thousands of trials underway around the world came to a halt as a result. Many projects are in the process of being adapted to continue remotely, facilitated by advances in telemedicine technology.

In a post-pandemic society the benefits of continuing remote research are apparent. Minimising the number of visits people make to hospitals, particularly those with medical conditions such as PD and PSP, is important. In addition, ease of access, with often the sole requirement being internet access, increases the possible number of participants for any given study. A familiar environment (home) enables the participant to feel more comfortable. By testing at home, stress levels will be reduced and concentration levels may well be increased. Stress consistently worsens parkinsonian symptoms, and avoiding it will give a more accurate picture of the subject's typical condition. If any issues are apparent with the data that have been collected when it is analysed, the investigators can contact participants to redo sections or the entirety of the visit remotely. Historically, with face to face visits this would be uncommon—especially if it involved patients driving hours to the test centre.

In addition, remote testing permits evaluation over much longer periods than the brief snapshot afforded in clinic. Some variables may even be measured continuously. Many symptoms wax and wane, under the influence of factors such as circadian rhythms or medication timing, or seemingly randomly. An accelerometer in the clinic can give a highly accurate measure of tremor at that moment, which is at the same time a highly *in*accurate representation of how bad that patient's tremor is in general.

This is a form of sampling error and may contribute greatly to noise in longitudinal measurements.

Challenges of remote testing include, amongst other issues, the importance of accurately placing sensors. All the advantages noted above are reliant on precise technology and subtle changes in movement. As such, patients—often with severe symptoms—may not be able to place the sensors upon themselves. When patients perform the same tasks in clinical settings, a researcher would attach the sensors and constantly troubleshoot. This shift in dynamic will add additional confounding factors to the data which need to be considered—heterogenous sensor placement. A solution could involve in-depth videos on correct placement. However these can be time intensive to watch (dramatically increasing the time needed to undertake the study at home) and patients—especially when elderly-might forget precise instructions.

Currently, there is a lot of work put towards developing protocols for running telemedicine and home monitoring testing as efficiently and as accurately as possible. Compliance with the technology used as well as with the suggested protocols is being tested worldwide. With advancements in technology such remote testing is being made possible and will, hopefully, prevent any further delays with future clinical trials.

Saccadic measurements require a headset to be used and operated by investigators with expertise so home testing with such a set up would be difficult. However work to repurpose webcams to accurately measure eye movements is already underway (Papoutsaki 2020). In addition, neural networks are being trained on data from eye-tracking equipment to pre-train models to enable transfer learning (Zemblys et al. 2018). The hope is that such models can then be reused, using transfer learning, to precisely track and measure eye movements as seen on webcam recordings and thus the possibility of measuring them remotely.

There are significant hardware design challenges and strategic choices to be made in the home monitoring of patients, particularly in large numbers. The use of consumer device technology is a key issue. The advantages of deploying a biomarker test as an application on a smartphone or tablet are obvious in terms of cost (no need to develop bespoke hardware) and scalability (the task could be undertaken by an essentially unlimited number of participants).

Despite these advantages, there also sacrifices to be made: Tasks that depend on measuring timing with millisecond accuracy may suffer when running on consumer devices with a typically 60 Hz screen refresh rate. Measurement of gait using the accelerometers built into smartphones in the pocket is appealing, because it can become a 'background task' for the patient requiring no special donning/doffing, and therefore excellent compliance can be expected. This said, the data processing needs to cleanly separate the motion of the device relative to the patient from the actual motion of the patient. This may be a fiendish computational task that could have been avoided by simply strapping on an IMU, inertial measurement unit, (which will also have better quality sensors). Which approach is best will depend on exactly what is to be measured and with what precision.

Case Study: Neurometrology

The NeuroMetrology group, at the University of Oxford, is predicated upon developing ways to accurate measure neurological disorders such as Parkinson's disease.

Most medical conditions can be rapidly and accurately quantified. For example, we can accurately measure the airflow rate in the lungs in asthma or the degree of narrowing of arteries in heart disease. However, we still measure many brain diseases using a clinical rating scale, a system of points assigned by an observer based on their impression of the person's condition. Such scales are subjective, i.e. two different people assessing the same patient may not score the patient equally, and they are also necessarily nonlinear, meaning that for example the difference between scores of 30 and 40 may not be the same as the difference between scores of 20 and 30. These things make analysis of changes over time difficult.

Parkinson's Disease and Progressive Supranuclear Palsy are both measured with rating scales. While currently available treatments for these diseases are symptomatic only, and do not have any preventive or disease-slowing effect, new disease modifying treatments for both are being sought and in due course will need to be subjected to clinical trials. The subjective nature of rating scales mean that trial results may become apparent less quickly than they would if we had quantifiable measures of disease state. Clinical trials are time extensive and expensive. Hence it is desirable to obtain salient results as early as possible so resources can be allocated to studies showing the most potential.

The OxQUIP (Oxford QUantification In Parkinsonism study) https://www.ndcn.ox.ac.uk/research/neurometrology-lab/research-studies/the-oxquip-study) began in 2016 and has been recruiting patients with Parkinson's disease and Progressive Supranuclear Palsy. In this study we follow patients with PD and PSP on a three-monthly basis over a two-year period. Using specialized testing equipment, we measure subtle abnormalities of movements of the body and the eyes. We are using a range of sensors including APDM Opal sensors to measure postural stability, timed up-and-go, and gait, Kinesia sensors which form an 'electronic UPDRS', saccadometers (oculometers that measure eye saccades), and tapping devices to measure the rate and rhythm of hand movements. These measurements produce data that is objective, quantitative, and on a ratio scale. Oculometers and wearable polyaxial accelerometers/gyroscopes yield very large numbers of data points rapidly and patients tolerate the tests well.

Due to the COVID-19 pandemic, we had to adjust our protocol towards telemedicine and continuous and home monitoring. We believe this will give a better overall picture of the patients' condition, and it will also permit the study to continue even despite COVID-19 related restrictions that prevent research clinic visits. To date it has been an excellent opportunity, to revisit the way we run some of our protocols as well as testing out what is possible in a home environment. Most digital technology has been focusing on research/clinic environments with expert teams running the tests. Home monitoring has introduced a significant change in how we record various movements of an individual while they are at the comfort of their home and importantly what the quality of the data is (including the level of compliance from patients). This is certainly a change that will persist in the years to come and the hope is for a hybrid of in person clinic visits, along with telemedicine and home monitoring.

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Chapter 23
Smart Sensors for Health Research and Improvement

Patricia Garatva, Yannik Terhorst, Eva-Maria Messner, Walter Karlen, Rüdiger Pryss, and Harald Baumeister

Abstract Sensors represent the prerequisites for data collection in the field of digital phenotyping and mobile sensing. Today, many sensors are connected over the Internet or feature advanced processing, thus provide smart functions that go beyond simple measurements. Embedded in everyday devices such as smartphones and wearables, smart sensors enable the collection of a vast amount of data in a natural setting and the unobtrusive real-time monitoring of people's lives. Initial empirical studies illustrate the possibilities and high potential of using ubiquitous smart sensors in health research. However, to realize the full potential, a deeper understanding of the underlying concept of smart sensors in health research is important. The present chapter aims to give a theoretical, non-technical introduction to the basic concepts of smart sensors in mobile health sensing. Hence, this chapter provides a brief overview of currently available sensors and proposes an overarching taxonomy. For the sake of simplicity, the focus of this chapter will be on smart mobile sensors, in particular those currently embedded in smartphones. Following this, we will briefly discuss what can be sensed and how health can be predicted from this sensor data. Additionally, we provide examples of research projects based on smartphone sensors, followed by an outlook on current challenges, future research perspectives, and potential clinical applications.

Keywords Digital phenotyping · Mobile sensing · Passive sensing · Smart sensors · Mobile sensors · Smartphone

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_23

23.1 Introduction

Digital phenotyping refers to collecting and analyzing data from digital traces (Insel 2017; Jain et al. 2015; Torous et al. 2016). So far, the most prominent endeavor of digital phenotyping is the approach of mobile sensing (Baumeister and Montag 2019). With mobile sensing, data is gathered from personal mobile devices (i.e., smartphones, smartwatches, and other wearables) and built-in sensors (e.g., GPS, microphone, accelerometer) with the aim of tracking health-related data (Lydon-Staley et al. 2019; Martinez-Martin et al. 2018; Torous et al. 2017). Accordingly, prerequisites for data collection are sensors.

To fully exploit the potential of mobile sensing, health-care researchers will need to collaborate with software engineers to discuss how their ideas can be implemented and to ensure that data collection with mobile devices is accurate and all-encompassing, respectively (Rowe 2019). Accordingly, to come up with future studies, health-care researchers must gain a deeper understanding of the underlying concept of passive sensing. We believe this is needed to improve study designs and research methodology.

Therefore, the aim of this chapter is to provide an introduction to the basic concepts of mobile sensing. Indeed, we do not aim to provide a comprehensive background on technical details (see, e.g., Majumder and Deen 2019; Odenwald 2019 for further reference), but we will give an overview of the main available sensors and introduce a general taxonomy for these. For a better understanding and the sake of simplicity, the primary area of focus will be on mobile sensors, in particular, but not limited only to those currently embedded in smartphones. What can be sensed and how health can be predicted will be briefly discussed, followed by some examples of how smartphone sensors are already used in health research. Lastly, some potentially promising future research perspectives will be discussed, followed by current challenges in the field of mobile sensing, including potential implications for health-care researchers.

23.2 Smart Sensors in the Field of Mobile Health Sensing

A sensor can be defined as a technology for measuring a physical characteristic, and hence depicting the source for raw data collection (Mohr et al. 2017; Su et al. 2014). Steady miniaturization of sensing technologies has made sensors more compact, lightweight, power-efficient, economical, and precise, which has led to a multitude of mobile devices (i.e., smartphones, wearables) with a high number of embedded sensors (Majumder and Deen 2019; Mohr et al. 2017; Sony et al. 2019).

In the light of a unified taxonomy for sensing human behavior and health, a first significant differentiation should be made regarding the interaction with the user that is needed for effective sensing: Sensors in mobile devices allow for passive sensing (does not require active user participation, e.g., acquiring GPS signals), active sensing [involves active user participation, e.g., ecological momentary assessment (EMA)], or sensing from metadata (a combination of passive and active data, such as the time it takes to finish the EMA survey) (Benoit et al. 2020; Majumder and Deen 2019). These sensors and combinations of sensing types can be used to observe everyday behavior, enabling researchers to measure data on location (e.g., from GPS signals), movement (e.g., from accelerometer or gyroscope), voice (from microphone), and contextual information (e.g., from light or temperature sensor), to name just a few (Mohr et al. 2017; Trifan et al. 2019). Furthermore, they can be used to measure physiological parameters such as heart rate, oxygen saturation, or respiratory rate (e.g., from image sensor or touch screen) (see e.g., Jonathan and Leahy 2010; Karlen et al. 2014, 2015; Karlen et al. 2012). In computer science, the difference between passive and active data in the context of mobile data collection is carried out by the flavors of participatory and opportunistic mobile sensing (Pryss 2019). However, the concepts shown in respective solutions less deal with health-care questions.

This can also be utilized in health-care settings and allows clinical researchers to infer data pertinent to the health of an individual, including the prediction of behavior patterns and personal characteristics (e.g., sleep, mood, physical activity), detection of clinical states [i.e., Parkinson's disease (Schwab and Karlen 2019), depression (Wahle et al. 2016), multiple sclerosis (Schwab and Karlen 2020), or schizophrenia (Fraccaro et al. 2019)], or monitoring of disease progression (i.e., risk for a depressive episode) (Majumder and Deen 2019; Martinez-Martin et al. 2018; Trifan et al. 2019). Thus, given these sensors no longer only perform simple measurements, but also provide classifications and foster intelligent decisions, we refer to them as *smart sensors*. Smart sensors can be defined as sensors that (1) are connected to the Internet and communicate with each other (i.e., through a smartphone or the Internet of medical things) to achieve intelligent tasks or (2) perform standalone high-level tasks independently such as classifications or adaptive sensing. Thus, the sensors are smart per se and not the mainframe computer that processes the data afterwards. Examples of smart sensors are accelerometers with step or fall recognition or cameras with face recognition, to name just a few. To conclude, smart sensors are more than physical sensors. In the following we will use the broad definition of smart sensors that encompass both definitions of (1) and (2) as the basis for our chapter.

23.2.1 Classification of Smart Sensors

Smart sensors can be divided into two groups: hardware- and software-based sensors. Hardware-based sensors are physical components built into a device (Android 2021). They obtain their data by directly measuring specific characteristics (e.g., for acceleration or rotation applied to the device; Android 2021). Software-based sensors derive their data from indirect measurements of processes, sourced from other hardware sensors or from software output (Android 2021; Mukherjee et al. 2016). Phone usage data (e.g., screen on time, duration of app usage) is one example of a software-based sensor that derives the information from software algorithms, mostly embedded in an application programming interface (API, e.g., Alvarez-Lozano et al. 2014).

Hardware-based sensors can be further classified into three different types of sensors: location, motion, and environmental sensors (Android 2021; Mylonas et al. 2013). Location sensors (i.e., GPS, magnetometer, proximity sensor) measure the current location of a device (Android 2021). Motion sensors (i.e., accelerometer, gyroscope, pressure sensor) are used to detect physical activity (Lima et al. 2019), and environmental-based sensors (i.e., microphone, light, image, humidity, temperature, or pressure sensors) are used to detect user's contextual information (Android 2021). Figure 23.1 illustrates the classification model for these sensors.

Both hardware- or software-based sensors can provide information related to a person (person-centric sensing) as well as the environment (environmental sensing), just as with its combination (person-environment-sensing) (Laport-López et al. 2020). The approach of person-centric sensing refers to the person as a sensing object (e.g., physical activity, mood, or sleep; Messner et al. 2019), while environmental sensing refers to the environment of the device as the sensing object (e.g., air pollution or traffic; Dutta et al. 2017; Laport-López et al. 2020; Sony et al. 2019). For health research, the person-environmental-sensing approach is of particular interest, as it could help to explore the complex interplay between subjects and their environment (e.g., the health impact of physical activity on the risk of having a depressive episode, social interactions; see Fig. 23.2).

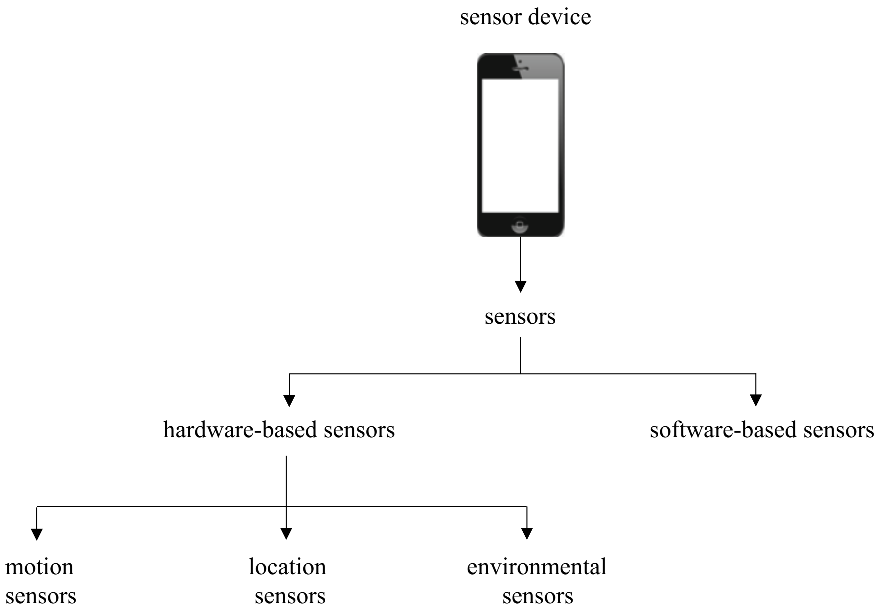

Fig. 23.1 Classification of sensors

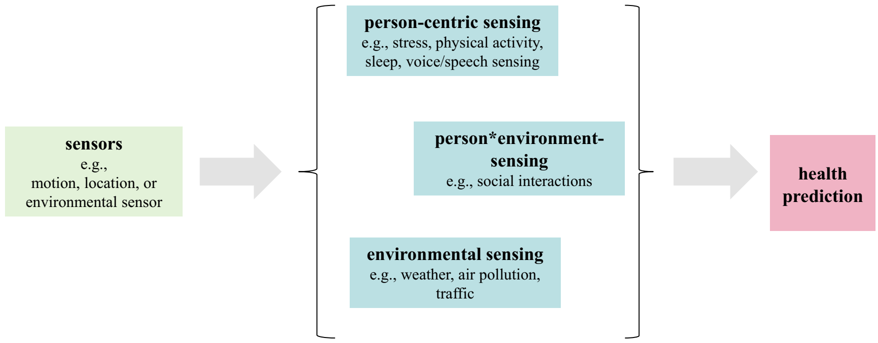

Fig. 23.2 From sensors to prediction of health

23.2.2 Overview of Smartphone-Based Sensors

Smartphones are of particular interest in the field of mobile sensing, as they often come with a number of embedded sensors, such as accelerometer, gyroscope, microphone, ambient light sensor, and GPS (see Fig. 23.3 for an overview) (Cornet and Holden 2018; Ferreira et al. 2015; Majumder and Deen 2019; Mohr et al. 2017). Besides, with more than three billion people worldwide using a smartphone (Statista 2020), smartphones have become ubiquitous in everyday lives (Cornet and Holden 2018; Mohr et al. 2017). As a result, it is possible to acquire large, longitudinal,

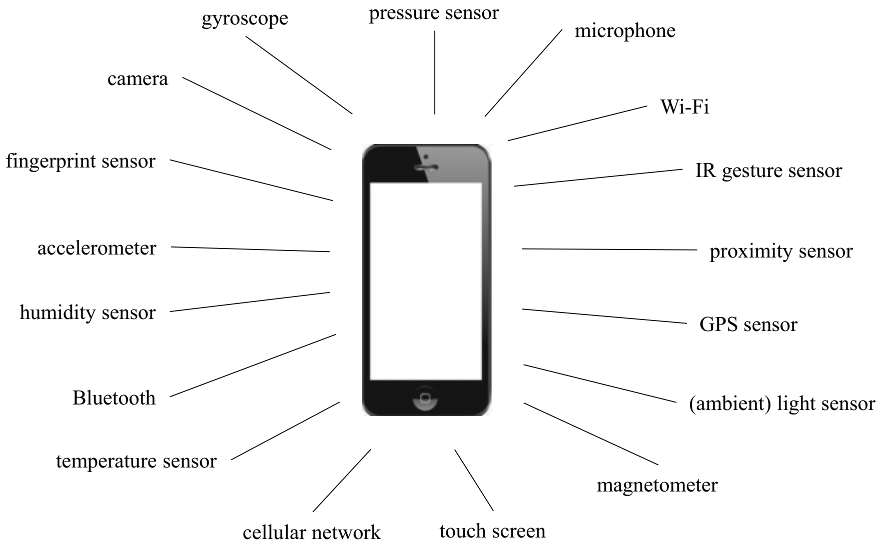

Fig. 23.3 Overview of currently available hardware-based sensors that most present-day smartphones possess

fine-grained, and representative datasets (Lydon-Staley et al. 2019; Majumder and Deen 2019; Torous et al. 2016). As people are carrying their mobile phones on or near them most of the time (Mohr et al. 2017; Montag et al. 2020), people's daily lives can be unobtrusively monitored in an everyday setting and data can be collected continuously in real-time (Ebner-Priemer and Santangelo 2020; Mohr et al. 2017; Sano et al. 2018; Trifan et al. 2019). Therefore, these smart sensors can enable health-care researchers to mitigate limitations associated with traditional assessment methods (i.e., questionnaires) (Messner et al. 2019; Proudfoot 2013). For example, while carrying a smartphone, it is possible to measure the location (mostly accomplished through a combination of GPS and WLAN), while, at the same time, accessing smartphone usage behavior features and gathering contextual information to identify a depressive episode (Moshe et al. 2021). Consequently, smartphones became a promising ecological health-monitoring tool and boost ecological validity (Majumder and Deen 2019; Mohr et al. 2017; Trifan et al. 2019). Some of the most important sensors are listed in Table 23.1, along with a brief description of their function.

23.2.3 From Sensors to Health Prediction

It is of great interest for clinical researchers to understand how large data sets composed of raw sensor data can be translated into clinically useful information to predict health and disease (Martinez-Martin et al. 2018; Mohr et al. 2017). Since there are many different models available in the literature depicting the process of digital phenotyping from sensor data to health outcomes (see, e.g., Lima et al. 2019; Mohr et al. 2017), we narrowed it down to three main steps: (1) data collection, (2) data pre-processing, and (3) data analysis. Thus, in the following section, the common steps are briefly explained.

Data collection: As stated above, the first step in the process of mobile sensing is collecting raw data from sensors (Lima et al. 2019; Martinez-Martin et al. 2018). While some information may not be uniquely collected by one sensor, almost all information can be collected when combined with enough other relevant sensors. Data collection is often performed using software installed on the device, such as AWARE (Ferreira et al. 2015) or INSIGHTS (Messner et al. 2019; Montag et al. 2019).

Data pre-processing: After data was successfully collected, the raw data has to be prepared for further analysis (Su et al. 2014). This includes cleaning the data, as health-care data are highly heterogeneous, noisy, inconclusive, and fragmentary (Miotto et al. 2018). In the next step, features can be extracted (Mohr et al. 2017; Su et al. 2014). Often, this consists of descriptive statistics of sensor time series (Lima et al. 2019). For example, raw data about phone usage may be converted into the number and duration of incoming calls or text messages, the average time spent on the phone (Mohr et al. 2017), or the number of the screen on/off times (Min et al.

Table 23.1 Summary of the main sensors and their function in the field of mobile sensing

Sensor	Function	Built-in
Accelerometer	Measures the acceleration applied to the device, including the force of gravity (9.81 m/s^2) and is used to classify movement and body position (AWARE 2021; Sano et al. 2018; Su et al. 2014)	Yes
Global positioning system (GPS)	Indicates the geolocation of a device by receiving signals sent by GPS satellites (Cornet and Holden 2018)	Yes
Gyroscope	Measures the angular velocity and rotation to detect direction of movement and recognition of activities (AWARE 2021; Lima et al. 2019; Su et al. 2014)	Yes
Microphone	Acquires external sounds of the environment in which the device is located (Cornet and Holden 2018)	Yes
Pressure sensor	Measures the ambient air pressure to detect the user's position (e.g., in- or outside; Su et al. 2014)	No
Proximity sensor	Measures the distance between an object and the front screen of a device (AWARE 2021; Cornet and Holden 2018; Su et al. 2014)	Yes
Temperature sensor	Measures the ambient temperature (Su et al. 2014)	No
Humidity sensor	Measures the ambient humidity (Su et al. 2014)	No
Magnetometer	Measures the strength of the geomagnetic field in which the device is located (AWARE 2021; Su et al. 2014)	Yes
(ambient) Light sensor	Measures the ambient illumination (Su et al. 2014)	Yes
Bluetooth	Detects surrounding Bluetooth-connected devices and enables data transmission between those (AWARE 2021; Cornet and Holden 2018)	Yes
Wi-Fi	Detects nearby Wi-Fi-enabled devices and logs the Wi-Fi sensor into a wireless network (AWARE 2021)	Yes
Cellular network	Detects surrounding cellular antennas and transmits the signal to the base station for communication (calls and text messages; Cornet and Holden 2018)	Yes
Touch screen	Measures screen interaction (speed, position, pressure)	Yes
Camera	Acquires images and videos, performs physiological measurements	Yes
IR gesture sensor	Measures gestures performed closely to smartphone	No

(continued)

Table 23.1 (continued)

Sensor	Function	Built-in
Fingerprint sensor	Detects a unique pattern as a fingerprint	Yes

2014). The purpose of this step is to reduce the noise and to foster accuracy (Lima et al. 2019; Su et al. 2014), but can also lead to loss in sensitivity.

Data analysis: The last step is the analysis of the pre-processed data. Data mining describes the actual process of analyzing data in terms of extracting (mining) knowledge from large amounts of data (Fayyad et al. 1996). Data mining in the context of mobile sensing is usually accomplished by machine learning (ML) algorithms, including the field of deep learning (DL) (Lima et al. 2019; Su et al. 2014). The goal of these data mining techniques is to identify patterns, trends, or correlations among potentially large datasets and to use the detected patterns to generate models (model building), that can make predictions about health (Lima et al. 2019; Miotto et al. 2018; Rowe 2019). In general, the process from raw data collection over data cleansing, data mining and model building to the prediction of relevant outcomes is addressed by Knowledge Discovery in Databases (KDD; see Fig. 23.4) (Fayyad et al. 1996). For health research, this procedure must be also carefully considered from the collection of raw sensor data to its usage to predict health outcomes. Although KDD is established in computer science for a long period of time, in health-care, some of the established methods have shown to be particularly suitable. For example, for health interventions, bandits and multi-arm bandits can be an enabler. Therefore, the steps presented by the field of KDD should be thoroughly followed, eventually be better able to distinguish which approach might be the best option for a problem at hand.

23.3 Exemplary Research for the Use of Smartphone-Based Sensors

Mobile sensing in the context of health research via smartphones results in a multitude of opportunities. In the following, we present a few empirical studies to highlight existing possibilities.

Saeb et al. (2015) collected sensor data on location (via GPS) and phone usage behavior (via software-based sensors) for two weeks (n = 28 adults) with the aim of detecting behavior patterns relevant to depressive symptom severity. They identified several behavior patterns, such as the mobility between favorite locations (r = 0.58, P = 0.012), a regular 24-h rhythm (r = −0.63, P = 0.005), and phone usage behavior (i.e., duration and frequency of use: r = 0.54, P = 0.011, and r = 0.52, P = 0.015, respectively), enabling the researchers to distinguish between people with depressive symptoms from those without with an accuracy of 86.5% (Saeb et al. 2015). Furthermore, a feasibility study collected data over two weeks

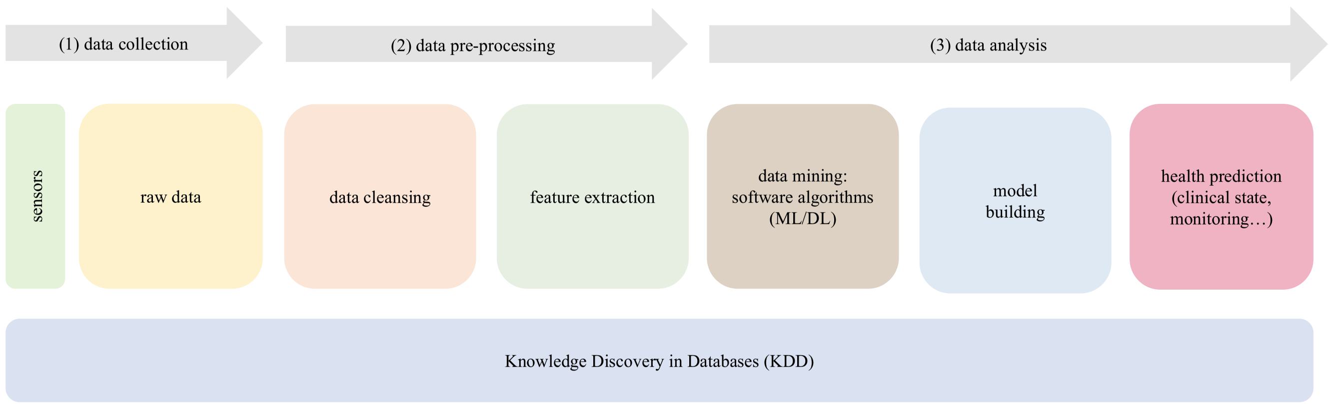

Fig. 23.4 The process of mobile sensing: translating raw, unprocessed sensor data into meaningful information about health. Correspondingly, there are three main steps: (1) data collection, (2) data pre-processing, and (3) data analysis. These steps are addressed by the field of Knowledge Discovery in Databases (KDD); however, in health-care research, they should be incorporated as well, which is often not pursued in the systematic way shown here

from the GPS sensor to detect social anxiety in 228 college students, showing that their location patterns (i.e., time spend at public vs private places, leisure activity) could meaningfully distinguish between individuals with high vs low social anxiety with an accuracy of 85% (Boukhechba et al. 2018).

Another possible application field of passive smartphone sensing was assessed by Messner et al. (2019): They investigated if there is an association between smartphone usage behavior (via software-based sensors) and self-reported well-being (stress levels, drive, and mood were assessed via EMA). Using the INSIGHTS app on 157 students for over eight weeks, they identified a negative association of smartphone usage behavior (e.g., total usage time, call duration) and self-reported stress, drive, and mood (Messner et al. 2019).

In addition, it is also possible to track physiological data: Using the image sensor implemented in the camera of smartphones, heart rate and heart rate variability can be estimated (Huang and Dung 2016; Jonathan and Leahy 2010). Besides, smartphone-based sensors enable to detect fall events using an accelerometer and gyroscope, assumed that mobile phones are worn close to the body (Cheffena 2015). Furthermore, several researchers showed that it is possible to passively monitor sleep patterns (i.e., sleep duration, sleep stages, sleep quality) by combining different sensors, such as the accelerometer (for movement), microphone (for ambient sound), ambient light sensor, proximity sensor, and smartphone-based data (such as screen on/off, apps running on the phone, battery status) with an accuracy between 65 and 90%. (Behar et al. 2013; Gu et al. 2014; Min et al. 2014).

23.4 Limitations of Mobile Sensing

Sensing with smartphones faces several limitations related to sensor hardware and the use of smartphones and other wearables devices in general. As smartphones are primarily consumer devices that come in many shapes and configurations, the quality and performance of the embedded technology varies strongly between models and even devices of the same model. Unlike medical devices that undergo good manufacturing practice (GMP) (Tarabah 2015), this is no longer the case for smartphones and their sensors. The control over hardware and software updates is with the device manufacturers and not the clinicians and researchers. The diverse specifications of sensors can lead to strong data variations (Stisen et al. 2015), and firmware updates can lead to altered behavior in sensing or data pre-processing which are hidden to the user, therefore introducing hidden bias in the analysis. Generalized data analysis models that can cope with such variations often loose specificity (Karlen et al. 2009).

The use of smartphones is under the control of the user and is strongly dependent on daily task. Therefore, only activities can be measured where the sensors are present. Furthermore, sensors are sensitive to noise and other systematic errors (Kalantar-zadeh and Wlodarski 2013), which in many cases is amplified during movements and extreme environmental conditions (i.e., heat, humidity). Due to the ubiquitous nature of mobile sensing, the user and the environment cannot be controlled and therefore, the uncertainty of the observational data can be high. Data can easily get corrupted and missingness is common (Miotto et al. 2018; Zhang 2021). This results in measurements that are available at irregular intervals and at arbitrary numbers, sampled over very long time periods (Schwab and Karlen 2019, 2020). Making sense of such data is challenging for human observers and computer algorithms. Therefore, good data cleaning or recovery algorithms are needed and advanced machine learning models are required to process such types of timeseries. Alternatively, missingness can be used as predictor for health outcomes (Che et al. 2018).

23.5 Future Directions and Implications for Clinicians

Sensors are becoming ubiquitous in everyday lives, as they are embedded in many mobile devices (i.e., smartphones, wearables; Mohr et al. 2017), which enables us to investigate large samples over a long period of time at rather low costs. Further, as mobile phones are already integrated into people's daily lives, they allow higher compliance through their unobtrusive character even in at-risk populations and foster ecological validity (Messner et al. 2019; Mohr et al. 2017; Saeb et al. 2015). Hence, they have opened exciting new opportunities for health research. A few exemplary research studies were presented, showing the feasibility of using sensor data (e.g., from the GPS, accelerometer, or microphone) via smartphones to predict various health outcomes (such as sleep, stress, and clinical states, e.g., depression or social anxiety). To accelerate these efforts, we have identified the following future directions, which we believe would be promising in health research.

In the future, it is conceivable that mobile sensing will provide diagnostic expert systems, enabling identification of clinically significant psychopathology (e.g., depression, Parkinson's disease) early in its development while running in the background of a smartphone (Messner et al. 2019; Saeb et al. 2015). However, such systems should be based on artificial intelligence (AI) (Montag et al. 2020). As AI-based systems are able to deal with Big Data more effectively, they offer the possibility of differential diagnostics in shorter periods of time. Further, they can leverage the continuous monitoring of disease progression (i.e., risk for a depressive episode) (Majumder and Deen 2019; Martinez-Martin et al. 2018; Saeb et al. 2015; Trifan et al. 2019). Additionally, these systems may allow for personalized treatment of patients, including predicting and monitoring the course of treatment and giving feedback to users and practitioners (Cornet and Holden 2018; Messner et al. 2019). Furthermore, this creates the possibility of just-in-time interventions, which provide patient-tailored and context-appropriate interventions (Cornet and Holden 2018; Nahum-Shani et al. 2018; Wahle et al. 2016). These future directions and benefits of mobile sensing we hypothesized about are summarized in Fig. 23.5.

Although research has already shown promising possibilities for how smart sensors can be used in the field of health research, so far, most empirical studies do not

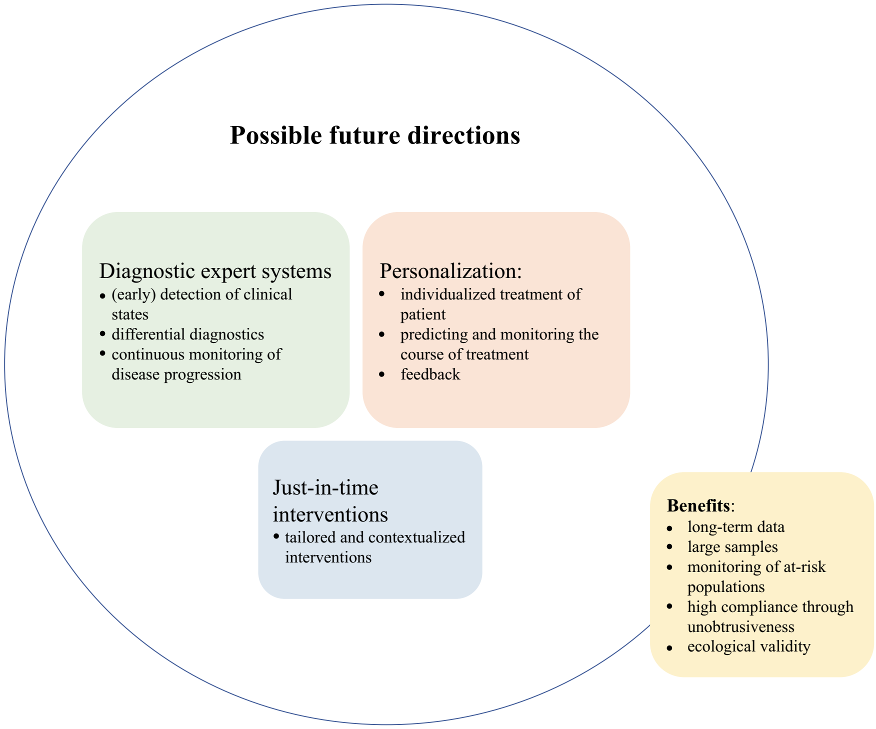

Fig. 23.5 Future directions in the field of mobile sensing and its promises for health research

go beyond proof-of-concept studies (Mohr et al. 2017); i.e., with small, hardly generalizable sample sizes. For instance, a recent systematic review reported an average sample size of 23.1 (SD = 27.9; median = 15; Cornet and Holden 2018). Future work should help to replicate the findings of other studies, to move from proof-of-concept studies to more robust and generalized findings in larger samples (Cornet and Holden 2018; Mohr et al. 2017). Furthermore, when using smartphones as a sensing device, the most commonly used sensors so far have been the accelerometer and the GPS sensor (Benoit et al. 2020; Cornet and Holden 2018; Trifan et al. 2019). Future work should additionally investigate other sensors (such as microphone or image sensor) in order to detect other health-related patterns. Besides, there may be an additional benefit if studies combine data from different sensors (e.g., the GPS, accelerometer, and software-based sensors). This could lead to more precise results in predicting health. Moreover, the smartphone represents the most used sensing device in mobile sensing with more than two-thirds of studies so far, but wearables (e.g., AppleWatch, FitBit, Oura rings) might be another promising source for mobile sensing (Cornet and Holden 2018; Laport-López et al. 2020; Moshe et al. 2021). Thus, future studies should consider collecting sensor data likewise via other wearable devices or at least combining smartphone-based assessment with other wearables where possible (e.g., biosensing; Dagum 2019). However, we stress the importance of having ecological validity in mind. In the future, expanding to other digitized areas of peoples' lives, such as smart homes (Liu et al. 2016) and smart cities (Dutta et al. 2017) is conceivable (Laport-López et al. 2020).

The current possibilities and these future research directions come with several challenges regarding the ethics and privacy of the collected data. The data collected by sensors can be considered sensitive, as it can be uniquely traced to distinct persons (Kargl et al. 2019; Mohr et al. 2017; Nicholas et al. 2019). Therefore, users need transparency about what data is shared, how it is retrieved, and when it is collected to decide whether they want to share it or not (Martinez-Martin et al. 2018; Nicholas et al. 2019). Thus, giving users possibilities to decide paired with featuring transparency might create trust in mobile sensing systems (Mohr et al. 2017). Furthermore, health-care researchers should consider not tracking everything possible, but only data that could carry benefits for the individual (such as feedback on the collected data) (Messner et al. 2019; Mohr et al. 2017). This may increase user's confidence in smart sensor systems.

The need of overarching considerations in the discussed field of sensor and mobile phone data usage for health-care questions has been recognized by important institutions like the WHO longer time ago. In 2016, a workshop organized by the WHO has presented a checklist for reporting of health interventions using mobile phones (Agarwal et al. 2016). The checklist emphasizes that technical solutions and procedures should be reported in addition to the analysis of data in order to foster evidence and comparability. Despite such existing works of the WHO, the presented field of using smart sensors for health research and improvement is still in its infancy. We therefore hope to foster the general guidance of health-care experts with the work at hand.

23.6 Conclusion

Growth in the field of mobile sensing will be more likely if clinical researchers have a deeper understanding of sensing (what can be sensed and how it is sensed). Hence, in this chapter, we gave a non-technical introduction to the basic concepts of smart sensors embedded in mobile devices. If we manage to overcome current challenges, and with having this new knowledge and the inferred implications for clinicians in mind, we believe that the promise for health research and improvement in the field of mobile sensing is enormous.

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Chapter 24
Smart Sensing Enhanced Diagnostic Expert Systems

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Abstract The ubiquitous presence of sensors (e.g., in smartphones) in our everyday life allows a constant real-time collection of data. This data has been successfully used in diagnosis and prediction of health outcomes and has the potential to improve health care. However, with data security and accountability as core requirements of medical applications, it remains a major challenge to integrate smart sensing information into the health care systems. One promising application is the integration into expert systems, in which smart sensing information is used to assist medical experts in their decisions. The present chapter aims to introduce expert systems, outline conceptual examples of such a smart sensing enhanced expert system, and summarize the evidence for smart sensing enhanced expert systems in health care. Lastly, the chapter will be concluded by discussing challenges in the field including ethical, privacy and security, and clinical issues followed by an outlook about future directions and developments.

Keywords Digital phenotyping · Smart sensing · Expert system

24.1 Introduction

The world-wide disease burden remains high and is even increasing in some diseases (James et al. 2018). Digitalization and personalization of health care is argued to be a promising way of improving medical health care (Alyass et al. 2015; Hamburg and Collins 2010; Obermeyer and Emanuel 2016; Wang et al. 2019). Due the ubiquitous presence of smartphones and other smart devices, smart sensing (=collection of

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*,
Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_24

digital markers and features via smartphones and other wearables) may offer a way to generate large data sets (Baumeister and Montag 2019; Messner et al. 2019; Mohr et al. 2017; Onnela and Rauch 2016). This could allow to draw conclusion about the health status, personality and behavior of an individual enabling personalization and improvements in health care (Ferreira et al. 2015; Messner et al. 2019; Mohr et al. 2017; Montag and Elhai 2019; Moshe et al. 2021; Onnela and Rauch 2016; Opoku Asare et al. 2021; Phan and Rauthmann 2021; Torous et al. 2019).

However, both the continuous data collection process of smart sensing and the multitude of sensors available in such devices lead to complex data sets. Utilizing the full potential of complex data sets requires powerful analysis methods. Especially, artificial intelligence (AI) and machine learning (ML) could achieve this task (Dwyer et al. 2018; Mohr et al. 2017; Opoku Asare et al. 2021). For instance, prediction models in mental health (e.g., for depression, bipolar disorder or social anxiety), oncologic care or alcohol use reached accuracy rates around 90% and higher when combining smart sensing data and ML (Bae et al. 2018; Boukhechba et al. 2017; Gruenerbl et al. 2014; Low et al. 2017; Opoku Asare et al. 2021). Timely and accurate diagnosis and symptom assessment is key to optimized health care pathways (Wurcel et al. 2019). These promising findings in classification (e.g., diagnosis) and prediction (e.g., symptom severity) tasks highlight the potential of smart sensing for the diagnostic process in future health care settings.

While these high accuracy rates are indeed promising the current evidence also shows highly heterogenous findings (Rohani et al. 2018). Small sample sizes further scrutinize the generalizability (Cornet and Holden 2018). Furthermore, accountability and transparency are crucial aspects in medical care, which have to be upheld in any smart sensing and AI-enhanced system (Bellotti and Edwards 2001; Elhai and Montag 2020; European Commission, Directorate-General for Communications Networks, Content and Technology, Ethics guidelines for trustworthy AI, Publications Office 2019). Therefore, fully automated diagnosis or treatment models without human oversight still remain a vision. However, as a first step smart sensing might be utilized in systems, which support medical experts' decisions (=expert systems), instead of being used as stand-alone medical applications.

24.2 Definition and Introduction to Expert Systems

In general, an expert system is a computer or web-based program to assist in a variety of problems or tasks (e.g., diagnosis) (Bennett and Doub 2016; Buchanan and Smith 1988). The concept and application of such systems exists for over four decades (Bennett and Doub 2016; Luxton 2014; Morelli et al. 1987; Wagner 2017). For instance, a program called MYCIN developed in the early 1970s is one of the earlier expert systems in the field of medicine, that was designed to support the identification of bacterial infections and the selection process for appropriate treatment (Shortliffe 1976). However, the applications of expert systems are by far not limited to health care (Bennett and Doub 2016; Luxton 2014; Morelli et al. 1987; Wagner

2017). A longitudinal content analysis of over thirty years of expert system case studies identified 311 individual studies evaluating expert systems in 26 different application areas (e.g., accounting services, financial services, manufacturing and others) (Wagner 2017). While it seems impossible to provide an exhaustive list of application areas, the underlying concept of an expert systems remains the same: First a knowledge base is used to derive a set of rules (e.g., if–then-rules), second these rules are applied to make interferences regarding individual input data (e.g., probabilistic recommendation), and third the interferences are presented in a user interface (Bennett and Doub 2016; Buchanan and Smith 1988).

Traditionally, expert interviews, observations, and protocol analysis have been used to obtain the knowledge base (Bennett and Doub 2016; Wagner 2017). Furthermore, rather simple statistical models or decision trees were applied to derive the set of rules (Bennett and Doub 2016; Wagner 2017). Rules are often combined to display or model the real-world (see Fig. 24.1) (Bennett and Doub, 2016; Buchanan and Smith 1988). However, this traditional approach to expert systems suffers from a core issue: The challenge to create and maintain the set of rules. Even with many rules integrated in a system there will always be an exception, that requires additional rules.

The ongoing trend of increasing available data from different sources may provide a solution to this issue: Advanced expert systems are more frequently built on large data basis, on which AI-models are trained to obtain complex but powerful algorithms (=rule sets) (Bellazzi and Zupan 2008; Bennett and Doub 2016; Hoogendoorn and

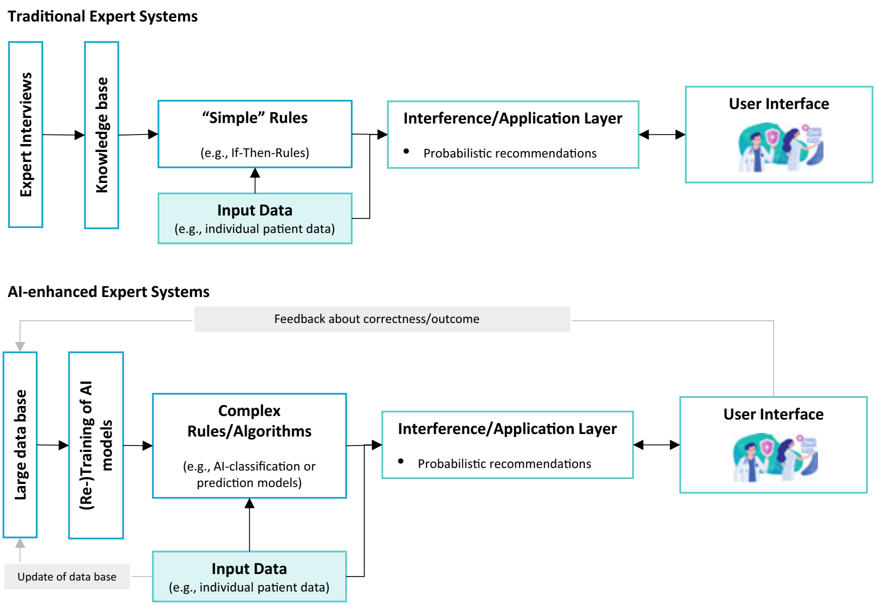

Fig. 24.1 Basic structure of expert systems

Funk 2018; Wagner 2017). Moreover, the underlying data basis can be constantly updated by input data (e.g., individual patient data, feedback from experts regarding accuracy) (see Fig. 24.1). This data-driven process may lead to the discovery of new rules or relationships between observable data and outcomes, which were unknown to experts. As a result, this could allow us to surpass classic expert systems by containing all possible expert-crafted rules.

24.3 Smart Sensing and AI-Enhanced Expert Systems in Health Care

In health care physicians, nurses, and other health care providers are constantly faced with making decisions. These include diagnosis of a disease, selecting between treatment options, personalized modifications of treatments, the supervision during treatment, evaluating treatment response and success—which apply analogously to prevention and aftercare. In an ideal world these decisions would be based on perfect information. However, in the present health care situation decisions must be made in limited time (e.g., 5–10 min physician meeting) and based on limited information (e.g., non-exhaustive potentially biased self-report about symptoms by the patient) (Ahmad et al. 2017; Irving et al. 2017). Furthermore, other factors such as availability of specialized physicians, time- and local restrictions, issues with insurance coverage along with stigma and other barriers might lead to situations where an individual with substantial symptom severity does not end up in health care at all (Andrade et al. 2014; Ebert et al. 2018; Nahum-Shani et al. 2018; Steele et al. 2021). Expert systems supporting the clinical decision process could make a major contribution to improve this.

As outlined before, smart sensing in combination with applying AI strategies can predict health states or health changes with high accuracy. This information could also be used and integrated in expert systems to improve the clinical decision progress (Alyass et al. 2015; Hamburg and Collins 2010; Mishra 2019; Obermeyer and Emanuel 2016; Steele et al. 2021; Wang et al. 2019). Possible areas include:

1. Assisted diagnosis and differential diagnosis: E.g., a system prompting a physician, that the patient at-hand is likely to have a depression or that highlights potential differential diagnoses with similar symptoms which should be further investigated.
2. Just-in-time interventions (JITI): With the real-time prediction of health status, symptoms and risk factors, physicians could be prompted to assign a suited treatment just in the moment of need.
3. Personalization of treatment and just-in-time adaptive interventions (JITAIS): Smart sensing and AI can be used to uncover the complex interplay between traits (e.g. personality) and biomarkers, behavior, state-of-mind, diseases, and treatment. Hence, systems could be implemented to suggest the most effective treatment to the physician, as predicted by AI. Thereby, physicians can adapt

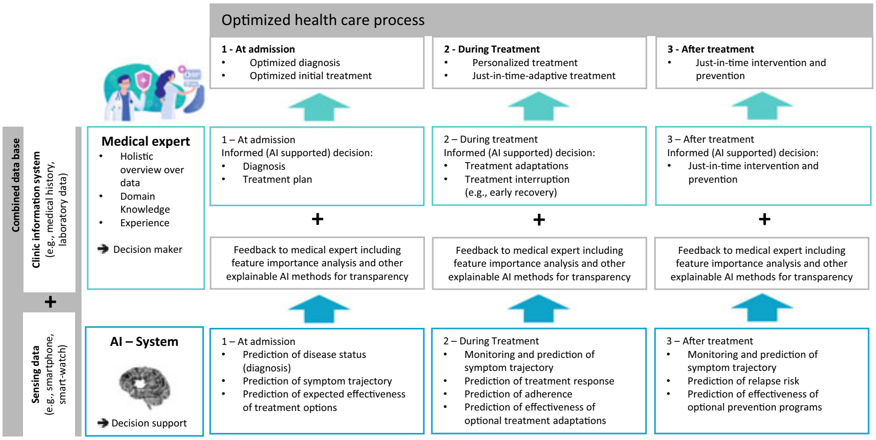

Fig. 24.2 Conceptual framework of a smart sensing and AI-enhanced expert system. *Note* Bullet points are non-exhaustive examples

a treatment plan based on this suggestion and their medical expertise (e.g., interruption of current treatment in case of early response or adding adherence-fostering measures).

These systems do not have to be limited to sensing data only. For instance, sensing data could be incorporated in data bases with other clinical information systems data (e.g., including medical history or laboratory data). For a visualization of how an exemplary system could look like see Fig. 24.2:

The systems outlined above could further be automated not involving a human at all, autonomously mirroring expert decisions (Bellotti and Edwards 2001; Chien et al. 2020; Mishra 2019; Steele et al. 2021). However, this goes hand in hand with ethical and legal questions, which are currently unsolved (i.e., accountability, data safety and technical standards; see Sect. 25.5. *Challenges and future directions*) (European Commission, Directorate-General for Communications Networks, Content and Technology, Ethics guidelines for trustworthy AI, Publications Office 2019; Steele et al. 2021). Hence, a fully automated smart sensing system diagnosing diseases, initiating, and modifying treatment is yet a utopic (or dystopic) vision. Nonetheless, if proven to be effective, the combination of human medical expertise, smart sensing, and AI may lay the foundation for future fully automated healthcare.

24.4 Evidence for Smart Sensing Enhanced Expert Systems in Health Care

As previously outlined AI-enhanced Expert Systems have a long standing history in medicine (Heathfield 1999). Computer-aided diagnosis including different sensor data has been developed across different medical application areas to various degrees (Yanase and Triantaphyllou 2019). However, many systems do not go further than the conceptual stage (Masri and Mat Jani 2012), lack empirical evidence (Heathfield 1999; Hossain et al. 2020), or do not make the transfer into clinical routine (Bennett and Doub 2016; Heathfield 1999). The usage of mobile device based smart sensing to assist medical diagnosis is even more specific and subject to the same barriers. However, there are a few examples worth emphasizing. One of the earliest papers proposing the inclusion of smart sensing for self-help was published in 2011 (Lee et al. 2011). Lee et al. (2011) suggested the usage of mobile self-diagnosis with a red flag system as an interface to attending physicians for danger symptoms in vital signs, thereby assisting the patients in self-health management and simultaneously improving the performance and quality of medical services.

Of all smart sensing features GPS in particular has been focused in many studies. On the subject of substance abuse for example, location sensitive triggered support for smoking (Naughton et al. 2016) has been investigated. The study implemented a Geofencing system with triggered context specific support messages in critical locations (i.e., locations where participants frequently smoke). Focusing on feasibility, they tried to connect location data and self-report behavior, as well as operationalize message prompts. The main problems were the small sample size (N = 15) and non-compliance in reporting smoking (Naughton et al. 2016). Another study used GPS initiated alerts at high risk locations (e.g., bars) for alcoholism relapse (Gustafson et al. 2014). The experimental smartphone condition (TAU +) reported fewer risky drinking days than the control group (TAU) and a significant difference in abstinence. Furthermore, the app usage predicted the number of risky drinking days. A strong suit of this study was the sample size of N = 349, which is rare in this field of research (Cornet and Holden 2018; Gustafson et al. 2014).

Continuing the prospect of JITIs, one study focused on sensing valence as proxy for stress combined with triggered ADHD specific parenting strategies (based on psychologist and behavioral therapist recommendations) (Pina et al. 2014). With a small sample size (N = 10), they found an increased in situ awareness, mindfulness of one's mood and suggested the usefulness of this app in supporting behavioral therapy (Pina et al. 2014).

Going one step further we see the application of just-in-time adaptive interventions (JITAIs) and personalized treatment. Thomas and Bond (2015) have addressed behavioral patterns in obese populations focusing sedentary behavior. Here, acceleration sensor-based prompts were used to reduce sedentary behavior. The study (N = 30) found higher engagement and more frequent prompts to result in higher levels of adherence (Thomas and Bond 2015).

Although rare, there are also examples for mental health expert systems. More specific, Wahle et al. (2016) conducted a pilot study with context-sensitive, sensing-based personalized treatment for depression. Proxies for social and physical behavior triggered context-sensitive and personalized interventions for people with depressive symptoms. A significant drop in symptomatology (PHQ-9) was observed for subjects with clinical depression at baseline and adherence $\geq$8 weeks. Furthermore, machine learning models performed better than the binary classifier. Promising research on predictive systems for stress, based on heart rate and heart rate variability, has been refined and theoretical data based approaches for consecutive JITAI have been developed (Clarke et al. 2017; Jaimes et al. 2014, 2016; Jaimes and Steele 2018) but no clinical trials have been published as of yet.

While the presented studies are promising, in clinical routine care, diagnosis, initiation and modification of treatment is within the authority of medical experts e.g. physicians guaranteeing medical accountability. To sustain accountability the lack of human intermediary between smart data assessment and AI interpretation of data remains a major challenge. Furthermore, overcoming long standing barriers concerning the implementation of systems into routine clinical practice are as relevant as ever. This includes barriers such the incorporation of systems into the wider professional and organizational context, coping with resistance of healthcare professionals, and managing and maintaining knowledge-based systems (Abbod et al. 2001; Heathfield 1999; Montag et al. 2020; Sindermann et al. 2020). Nonetheless, studies focusing on potential ways of automation and towards medicine 4.0 are important and may lay the foundation for significant improvements in health care (Kelly et al. 2019; Martinez-Martin et al. 2021; Mohr et al. 2017; Steele et al. 2021).

24.5 Challenges and Future Directions

The first fundamental prerequisite towards the application of smart sensing and AI-based expert systems is the acceptance of smart sensing and its incorporation into health care (Ahmad et al. 2021; Gao et al. 2020; Nicholas et al. 2019). Both the sensor data type (e.g., sleep data, physical activity, location) as well as the recipient of the data (e.g., physicians, electronic health record, family) are highly impacting upon the acceptance towards sensing data (Nicholas et al. 2019). For instance, the acceptance to share sensor data with a physician ranges from about 89% for sleep data to only 58% for location data (mood 82%, physical activity 77%, social activity 73%, communication logs 64%) (Nicholas et al. 2019). The acceptance to include this data into health records is even lower (e.g., location 50%, communication logs 52%) (Nicholas et al. 2019). In addition, lacking trust into AI and the absence of humanistic care factors are major barriers to acceptance of AI-based systems (Gao et al. 2020; Kelly et al. 2019; Montag et al. 2020; Sindermann et al. 2020). Only if these challenges are addressed and the acceptance towards smart sensing and AI-based expert systems is increased, a positive impact on health care can be expected.

Secondly, privacy and data security are key when it comes to smart sensing. Due to the multitude of sensors highly sensitive predictions can be made (e.g., diagnosis), which may even be unknown at the time of data collection (e.g., the predictive power of some data points will only be discovered later) (Dwivedi et al. 2019; Martinez-Martin et al. 2021; Stanley and Osgood, 2011). Furthermore, this data is often collected over a long period allowing even more conclusions. Hence, the data may lead to the identification of a person and also bares the risk of public exposure of personal information (e.g., health status) (Martinez-Martin et al. 2021). Measures to ensure privacy, transparency, data security, and prevent potential misuse of data are highly needed—as also highlighted by the European General Data Protection Regulation (The European Pariliament And The Council Of The European Union, 2018). Universal standards have to be developed before these systems can be enrolled into health care (Dwivedi et al. 2019; Kelly et al. 2019; Martinez-Martin et al. 2021). Up to date there is no licensed sensing system according to the medical device regulation (Ferreira et al. 2015; Montag et al. 2019; Moshe et al. 2021; Ranjan et al. 2019; Torous et al. 2019).

Speaking of the medical device regulation another issue arises. As outlined above, in an expert system data is constantly collected regarding the accuracy and predictive power (e.g., agreement between expert decision and AI-based classification, or predicted trajectory and actual trajectory). This data would be highly valuable for the further development and improvement of the system. It would be ideal if the data could be used for improvements in real-time (e.g., feeding the data into the underlying algorithms for re-training purposes). However, according to the medical device regulation a medical product is licensed at its current state and does not allow for continuous updates or changes of the product (i.e., optimizing the underlying algorithms) without additional validation. As a result of this and the elaborated accompanying regulations and obligations of the validation process improvements of expert systems might be slowed down. The achievement of robust regulations and rigorous quality control, whilst enabling performance monitoring and improvements poses a challenge in the field. Guidelines regarding the balance of optimizing algorithms and medical regulation need to be further developed (Kelly et al. 2019).

Furthermore, it has to be ensured that a smart sensing-based expert system is fair (Martinez-Martin et al. 2021; McCradden et al. 2020; Rajkomar et al. 2019; European Commission, Directorate-General for Communications Networks, Content and Technology, Ethics guidelines for trustworthy AI, Publications Office 2019). Fairness can be operationalized in different ways such as, that (1) protected attributes (e.g., gender, race) are not used for predictions (=anti-classification), (2) predictive performance is equal across groups (=classification parity) or 3) outcomes are independent of protected attributes given a risk score (=calibration fairness) (Corbett-Davies and Goel 2018). Applying these definitions to medical healthcare shows that fairness is often not achieved (e.g., racial bias in the management of health) (Char et al. 2018; Corbett-Davies and Goel 2018; McCradden et al. 2020; Obermeyer et al. 2019).

Lastly and maybe most importantly, sample bias and overfitting (Corbett-Davies and Goel 2018; Khoury and Ioannidis 2014; Riley et al. 2016), along with the limited evidence regarding smart sensing based expert systems (see Sect. 24.3), as well as the heterogenous findings in smart sensing (e.g., Cornet and Holden 2018; Rohani et al. 2018) pose a major challenge towards the implementation of smart sensing based expert systems into health care. Fusing existing psychological and clinical theories with machine learning techniques may offer a potential first step to solving these issues by reducing spurious findings and increasing the generalizability of findings (Elhai and Montag 2020).

Despite these issues in the field, future visions of smart sensing enhanced expert systems are too promising to be ignored. Visions range from improvements in diagnosis (Lee et al. 2011), continuous assessment of data, AI-based processing and calculation of complex causal relationships (Hofmann et al. 2016), to just-in-time interventions and personalization of treatment (Mohr et al. 2017; Steele et al. 2021). Further studies in the field are highly needed to realize the promising vision of smart sensing and AI-based expert systems (Kelly et al. 2019; Martinez-Martin et al. 2021; Rohani et al. 2018; Steele et al. 2021).

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Chapter 25
Ecological Momentary Interventions in Public Mental Health Provision

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Abstract Many people who suffer from mental disorders do not have access to adequate treatment options and the use of, and access to, prevention and mental health promotion remains limited. The rapid advances in digital technology make a compelling case to help deliver and implement evidence-based interventions in areas of public mental health provision (i.e., mental health promotion, prevention, and treatment of mental disorders). Ecological Momentary Interventions (EMIs) represent a powerful approach that enables provision of adaptive and personalised intervention components. EMIs build on principles of Ecological Momentary Assessment (EMA) and are centred around the dynamics of individuals' experience and behaviour, and their interaction with contextual factors in daily life. They offer a unique opportunity to deliver personalized interventions that are tailored to what individuals need in a given moment, context, and setting. This chapter explores the conceptual framework within which EMIs are defined, outlines their current applications, and provides an outlook of technology-enabled mental health care.

Keywords Ecological momentary assessment · Experience sampling method · Ecological momentary intervention · Mobile health · Digital intervention · JITAI · Mental health · Psychopathology · Public mental health

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_25

25.1 Introduction

Many individuals with mental disorders do not have access to adequate treatment options and often find themselves not reaching full clinical remission after treatment completion (Henderson et al. 2013). In many countries, access to mental health care is still limited by long waiting times, restrictive insurance policies, and difficulties in referring patients to mental health professionals (Kular et al. 2019; Bucci et al. 2019). This discussion is especially pertinent in light of the COVID-19 pandemic, which has been found to have immediate as well as prolonged effects on mental health, and to further reduce individuals' access to mental health services (Soron et al. 2020; Rauschenberg et al. 2021a, b). The rapid advances in digital technology make a compelling case to help reach, deliver, and implement evidence-based interventions (Kazdin and Blase 2011) and to offer low-threshold entry points to mental health services (Balaskas et al. 2021; Montag et al. 2020a). There is also emerging interest in using digital tools for extending the access to, and personalisation of, interventions beyond clinical settings, including the development and implementation of digital mental health promotion and prevention programs (Rauschenberg et al. 2021b; Ebert et al. 2017; Myin-Germeys et al. 2016).

Technology-enabled mental health services encompass telemedical, internet-based (eHealth), and mobile-based mobile Health (mHealth) (Rauschenberg et al. 2021b, 2022; Ebert et al. 2018) interventions. These digital interventions provide a plethora of novel opportunities for researchers and clinicians alike, including the possibility of providing integrative, person-tailored mental health services (Bucci et al. 2019). The concept of blended care is important in this regard (Bell et al. 2018; Aubel et al. 2020) and refers to the integration of digital interventions with on-site face-to-face therapeutic sessions (Erbe et al. 2017). There is accumulating meta-analytic evidence that blended care may be as effective as standard care in treating mental disorders while requiring significantly fewer resources when fewer face-to-face-sessions are required (Erbe et al. 2017). In line with these findings, digital interventions have been found to be most effective when they incorporate social components (e.g., personal contact with a mental health professional, online forums, peer support) and strategies to promote adherence (e.g., gamification elements) (Rauschenberg et al. 2021b). Studies also indicate that when digital tools are used in conjunction with routine mental health care, individuals' engagement in their own recovery processes may be increased (Erbe et al. 2017). However, when and for whom these measures for enhancing adherence, engagement, and recovery are most beneficial is currently largely under-researched. Given the rapid development of new technological solutions and, with regard to the present book, in particular smart sensing and digital phenotyping approaches, next generation digital mental health interventions might provide the means for this kind of personalisation providing an intervention at a time and in a situation when it will likely be most beneficial for a specific person. Hence, these so called Ecological Momentary Interventions (EMIs) or Just-in-Time-Adaptive-Interventions are one specific field of applied smart sensing and digital phenotyping.

25.2 Ecological Momentary Interventions (EMIs)

More recently, digital interventions, mHealth interventions in particular, have begun to incorporate more interactive and adaptive elements by using various forms of active and passive data collection to inform the delivery of treatment components, of which EMIs (Myin-Germeys et al. 2016, 2011; Reininghaus 2018; Heron and Smyth 2010; Patrick et al. 2005) represent a powerful approach. EMIs provide a window of opportunity for real-world, real-time, interactive, adaptive, and personalized interventions that are centred around the dynamics of individuals' experience and behaviour, and their interaction with contextual factors in daily life (Reininghaus 2018; Heron and Smyth 2010; Patrick et al. 2005). EMIs are designed to deliver person-tailored digital interventions when they are most needed, at the right time and in the right context (Myin-Germeys et al. 2016; Heron and Smyth 2010), outside of clinicians' offices or standard settings of mental health promotion and preventive interventions. The delivery of intervention components is informed by designs and principles of ecological momentary assessment (EMA) or, synonymously, experience sampling methodology, which enables real-time processing of fine-grained intensive longitudinal data collected via mobile devices (Myin-Germeys et al. 2016, 2018; Palmier-Claus et al. 2011; Reininghaus et al. 2016a). Thus, EMIs build on and extend the extensive knowledge base and principles of EMA (Myin-Germeys et al. 2016, 2018; Reininghaus 2018) and are particularly well suited to targeting candidate risk and resilience mechanisms that have been implicated in the development of a variety of mental health problems, including individuals' stress sensitivity in daily life (Reininghaus et al. 2016b, 2016c; Rauschenberg et al. 2021c; Paetzold et al. 2021).

More specifically, in a typical EMI, intervention components are offered according to event-contingent, time-contingent, or hybrid EMA design principles and sampling strategies, building on long-standing methodological insights and a large body of evidence from over twenty years of EMA research (Reininghaus 2018; Myin-Germeys et al. 2018). Further, individuals are asked to complete brief EMA questionnaires on moment-to-moment experiences, behaviours, and contexts encountered during the course of daily life. This may include their current positive or negative affect, symptom domains, minor stressors, activities, or social contexts, as the term EMA is commonly used (Myin-Germeys et al. 2018; Palmier-Claus et al. 2011; Csikszentmihalyi and Larson 2014; Larson and Csikszentmihalyi 2014; Os et al. 2017), but also passively collected multimodal data from built-in or add-on mobile sensors (e.g., accelerometer, Global Positioning System, electrocardiogram) to assess other variables such as mobility, physical activity, heart-rate variability, and sleep (Maher et al. 2019), which may be referred to as multimodal EMA but is also called mobile or smart sensing in the present book. If predefined criteria are met (e.g., increased momentary event-related stress or decreased physical activity), intervention components are delivered via a dedicated smartphone app. In addition, the EMA data collected during an EMI can be used to provide real-time monitoring of symptoms and behaviours in order to generate personalized feedback on subjective experience and behavioural patterns that can be used by clinicians to further personalize face-to-face treatment sessions (Rauschenberg et al. 2021) or to assist individuals in gaining insights into their own mental and physical health while going about their daily lives. These novel capabilities for monitoring symptoms and behavioural patterns, which are frequently referred to as digital phenotyping (Insel 2018; Montag et al. 2020b), have also been proposed for use in predicting illness trajectories (e.g., relapse of symptoms) or identifying early warning signals (Leemput et al. 2014; Wichers et al. 2019), but the evidence base for these applications still remains limited (Barnett et al. 2018). Recent efforts, although still in its infancy, also attempt to integrate data on pathophysiological biomarkers that have been found to be associated with mental health outcomes (Lorenz et al. 2019; Fraccaro et al. 2019; Cella et al. 2018; Economides et al. 2020).

Many eHealth and mHealth interventions which have been developed and evaluated in previous years do not actively use real-time processing of multimodal data to inform treatment delivery, while EMIs often use primarily time-contingent (or hybrid) sampling schemes with a fixed or random time schedule to increase representativeness of assessed target constructs, leave individuals fairly uninterrupted in their daily lives, and offer intervention components when they are most needed (Myin-Germeys et al. 2018). The types of data collected considerably vary depending on the objectives of the intervention and targeted mechanisms and outcomes. Moreover, within its theoretical foundation, EMIs make the key assumption that mental health is linked to, and modifiable in, everyday contexts and interactions in the social world and, consequently, aim to translate robust findings on candidate mechanisms of change and their impact on mental health (Reininghaus et al. 2016b, 2016c; Rauschenberg et al. 2021c; Domhardt et al. 2021a, 2019, 2020; Steubl et al. 2021) to inform novel intervention strategies (Reininghaus 2018). Thus, EMIs build on extensive EMA research and are designed to specifically target candidate mechanisms and mental health outcomes in daily life (Reininghaus et al. 2016a), including stress sensitivity, threat anticipation, aberrant salience, and self-esteem (Reininghaus et al. 2016a, 2016c; Rauschenberg et al. 2021c, 2017, 2021d; Daemen et al. 2020). This also enables testing of ecological interventionist causal models (Reininghaus et al. 2016a) by examining whether modifying candidate mechanisms produce downstream lasting changes on mental health outcomes. The benefits of these models, applied in the context of randomized controlled trials, are at least two-fold: on the one hand, they allow to examine important criteria for establishing causality such as association, temporal order, experimental evidence, and sole plausibility in daily life, outside the research lab (Reininghaus et al. 2016a; Susser et al. 2006; Susser 1991). On the other, they provide robust evidence whether the experimental manipulation method (i.e., the EMI) is an effective intervention technique.

EMIs continue to expand alongside other digital approaches and frameworks in the field. For example, more recently, just-in-time-adaptive-interventions (JITAIs) (Klasnja et al. 2015; Nahum-Shani et al. 2018), which emphasize the adaptive nature of digital interventions by operationalizing tailored assessments and aiming to deliver intervention components "just-in-time", have been conceptualized as a mostly synonymous concept to EMIs. EMIs actively use real-time EMA data to further tailor intervention components and the timing of delivery to individuals' current needs and context. This includes relatively simple if–then formulas as well as more sophisticated machine learning algorithms. For instance, there have been recent efforts to use machine learning techniques to assign intervention components of EMIs based on recurrent neural networks (RNNs; (Rauschenberg et al. 2021a; Koppe et al. 2019)), which could be leveraged to predict individuals' responses to specific exercises and offer context-dependent and customized digital interventions. There are differing elements that have been suggested to lay at the forefront of these and other cutting edge digital interventions, namely, well-defined distal and proximal therapeutic outcomes, decision points and rules, intervention components with a strong theoretical foundation, and the possibility for tailoring used EMA indicators (Myin-Germeys et al. 2016; Reininghaus 2018; Reininghaus et al. 2016a; Nahum-Shani et al. 2018; König and Renner 2019; Schick et al. 2021; Smyth and Heron 2016). Overall, exciting opportunities for translating extensive time series data and adaptive sampling schemes into meaningful innovations in mental health care are being developed.

25.3 EMIs in Public Mental Health Provision

EMIs and related mHealth interventions can be used across the entire spectrum of public mental health provision, which includes the following four domains: (1) mental health promotion; (2) stigma reduction and mental health literacy; (3) prevention, including (a) indicated prevention targeted at high-risk individuals, (b) selective prevention targeted at subpopulations at raised risk, and (c) system-level prevention targeted at a diverse range of settings; and (4) delivery of mental health services (inpatient, outpatient, and community-based treatment programmes and services (incl. aftercare)), for people with mental disorders (Rauschenberg et al. 2021b; Montag and Rumpf 2021). Some evidence-based interventions have been translated into EMIs and other types of mHealth interventions, including techniques and exercises frequently used in cognitive behavioural therapy and third-wave cognitive behavioural therapy (Balaskas et al. 2021; Myin-Germeys et al. 2016; Reininghaus 2018; Heron and Smyth 2010; Colombo et al. 2019; Bell et al. 2017; Loo Gee et al. 2016; Schueller et al. 2017; Smith and Juarascio 2019; Versluis et al. 2016). These interventions show great promise, particularly when adherence is promoted and social components such as blended care or peer support are incorporated (Rauschenberg et al. 2021b). The use of EMIs and related mHealth interventions are being researched across a variety of mental health domains, including depression (Aubel et al. 2020; Colombo et al. 2019; Bastiaansen et al. 2020; Depp et al. 2015; Kramer et al. 2014; Harrer et al. 2021), anxiety (Daemen et al. 2020; Schick et al. 2021; Smyth and Heron 2016; Loo Gee et al. 2016; Schueller et al. 2017; McDevitt-Murphy et al. 2018; Morgieve et al. 2020; Newman et al. 2014; Nguyen-Feng 2019; Nguyen-Feng et al. 2019; Pramana et al. 2014; Walz et al. 2014), attention deficit/hyperactivity disorder (Flujas-Contreras et al. 2019; Pina et al. 2014; Schoenfelder et al. 2017), psychosis (Bell et al. 2018, 2017; Hanssen et al. 2020; Reininghaus et al. 2019; Myin-Germeys et al. 2021), substance misuse (Businelle et al. 2016; Hebert et al. 2018; Merkouris et al. 2020; Riordan et al. 2015; Shrier et al. 2018; Wright et al. 2017), and eating disorders (König and Renner 2019; Anastasiadou et al. 2018; Boh et al. 2016; Brookie et al. 2017; Heron 2011; Juarascio et al. 2015). However, the effectiveness and cost-effectiveness, potential adverse effects, implementation, uptake and reach of most EMIs still remain to be established, given the recency and innovative nature of this approach.

While some evidence exists for the effectiveness of EMIs and other types of mHealth interventions for mental health promotion (e.g., increasing physical activity (Boehm et al. 2019; Bort-Roig et al. 2014; Feter et al. 2019; Kim and Seo 2019; Rose et al. 2017; Muntaner et al. 2016), stress appraisal (Loo Gee et al. 2016; Donker et al. 2013), improved sleep (Saruhanjan et al. 2021) in general population samples, and stigma reduction (Peter et al. 2021; Mills et al. 2020)), the overall number of well-powered, high-quality studies remains limited. Furthermore, a significant difference exists between publicly available mHealth apps in major app stores, for which there is no or very limited evidence of their effectiveness (Larsen et al. 2019; Sander et al. 2020; Terhorst et al. 2018; Domhardt et al. 2021b) and EMIs developed by research groups. Most studies to date have investigated the effectiveness of EMIs for individuals with various mental disorders. For example, the 'FOCUS' intervention (Ben-Zeev et al. 2014) is a multimodal digital intervention for people suffering from psychosis spectrum disorders, including schizophrenia and schizoaffective disorders. Over the course of one month, participants were prompted to answer short questions about their mood and symptoms three times per day. Based on the content of these assessments, FOCUS delivered person-tailored interventions which primarily covered the following domains: (1) strategies for coping with auditory hallucinations (e.g., distraction, cognitive restructuring, and hypothesis testing techniques), (2) anxiety and depression management (e.g., relaxation techniques, behavioural activation, and other supportive content), (3) sleep, and (4) social functioning. These interventions were also available 'on-demand' at any time and FOCUS has been shown to be feasible and acceptable in individuals with psychosis (Ben-Zeev et al. 2014, 2018). The Acceptance and Commitment Therapy in Daily Life ('ACT-DL') trial (Reininghaus et al. 2019; Vaessen et al. 2019), translated ACT principles and exercises into an EMI delivered via an mHealth app, with the goal of targeting putative psychological mechanisms such as stress sensitivity, psychological flexibility, and reward experience in individuals with early psychosis. ACT-DL modules included creative hopelessness, acceptance, self-as-context, cognitive defusion, and defining values. In the experimental group, patients are prompted with a short questionnaire on their current mood, activity, and complaints eight times per day at semi-random moments. ACT-based exercises tap into these experiences or practice general ACT skills previously learned with a clinician. While the feasibility of ACT-DL has been documented (Vaessen et al. 2019), findings from a multi-centre RCT on its efficacy (including at 6-month and 12-month follow-up) are now available (Myin-Germeys et al. 2021). A recent uncontrolled pilot study (Rauschenberg et al. 2021d) examined a compassion-focused EMI for emotional resilience ('EMIcompass') in help-seeking youth experiencing psychotic, depressive, or anxiety symptoms as well as at high-risk individuals. Three sessions with a psychologist were combined with a three-week EMI delivered via an mHealth app. During the intervention, participants answered short EMA questionnaires prompted six times per day on four days a week. High ratings on current stress, affective disturbances (anxiety, mania, depression), and/or threat anticipation in the EMA triggered real-time delivery of interactive tasks for participants to complete. The findings from this pilot study indicate that delivering compassion-focused intervention components via an mHealth app (e.g., compassionate image and writing, emotions as a wave, and breathing exercises) may reduce individuals' stress sensitivity in daily life as well as various psychopathological domains in help-seeking youth (Rauschenberg et al. 2021d). The clinical feasibility and safety of EMIcompass were acceptable, with participants reporting moderate to high satisfaction with the intervention protocol and no adverse events (Rauschenberg et al. 2021d). Initial signs of efficacy of the EMIcompass study are currently being evaluated in an exploratory randomized controlled trial. The findings will be published in 2022 (Schick et al. 2021).

Additionally, other current projects address various areas of EMI-based public mental health provision. This includes the recently launched living lab artificial intelligence for personalized digital mental health promotion and prevention in youth ('AI4U'), which aims to develop, optimize, evaluate, and implement digital machine learning-informed EMIs in routine public mental health provision by adopting a transdisciplinary approach involving users from the target population and relevant stakeholders in all stages of the research process (Rauschenberg et al. 2021a). The 'SELFIE' trial focuses on selective prevention and aims to investigate the efficacy of a novel, youth-friendly, transdiagnostic EMI for improving self-esteem in youth with prior exposure to childhood adversity in a multi-centre randomized controlled trial (Daemen et al. 2020). The eSano Online-intervention platform (Kraft et al. 2021) currently focuses on its smart sensing extension in order to allow for EMI-based personalisation of several already evidence-based mental- and behavioural health interventions. Lastly, the project 'IMMERSE' (Implementing Mobile Mental health Recording Strategy for Europe) (IMMERSE, 2021. Available from https://immerse-project.eu) aims to advance person-centred mental health care by implementing a digital mobile mental health tool for EMA-based monitoring and feedback, mobile sensing, and machine learning in routine clinical care pathways. In close collaboration with stakeholders, implementation strategies, outcomes, processes and costs will be assessed and public health and economic impact evaluated in a cluster Randomized Controlled Trial (cRCT) at 8 sites in 4 European countries (IMMERSE, 2021. Available from https://immerse-project.eu).

25.4 Future Outlook

EMIs enable adaptive, real-time, and real-world transfer of intervention components into individuals' daily lives, providing a unique opportunity to deliver personalized interventions across the entire spectrum of public mental health provision. They are tailored to the specific needs in a given moment and context by leveraging real-time processing of multimodal EMA data (Koppe et al. 2019). However, critical issues remain in the broader context of digital mental health care in general and EMIs in particular. This includes a lack of knowledge about the long-term effects, efforts to close the gap between research and clinical practice, and the inclusion of user and other stakeholder experience as a critical component in the development, and evaluation and implementation. Notably, there still seems to exist a gap between people who do and do not have access to digital tools on which prompts can be delivered (known as the "digital divide"), including a lack of physical access to the internet and digital literacy (Bucci et al. 2019). Stakeholder-centred designs allow EMIs and other digital interventions to be developed as technology-enabled services rather than stand-alone products, in the relevant service and health care contexts and accompanied by supportive organisational and policy innovations to ensure scaling of digital interventions is successful (Mohr et al. 2017). There is also a need to advance our understanding of the cost-effectiveness and the theoretical underpinnings of EMIs, particularly in relation to putative mediators and mechanisms of change. For example, an important factor contributing to lower dropouts and better clinical outcomes is the therapeutic alliance (Windle et al. 2020). As a result of less face-to-face contact with a mental health care provider, this important contributing factor may warrant further attention in the context of technology-enabled mental health services and interventions (Hollis et al. 2018; Torous and Hsin 2018). However, unfavourable outcomes can be minimized by carefully considering elements such as selection of hardware/software and usability of EMIs, as well as flexibly increasing or decreasing digital components by implementing principles of graded traditional care. This is linked to the remaining challenge of finding more advanced ways to use actively and passively assessed data (or approaches of digital phenotyping) to inform the delivery of different intervention components. In the next 20 years, integration of differing technologies in EMIs will likely mature into smaller devices and more sophisticated digital interventions such as digital assistants (Abd-Alrazaq et al. 2019) with the ultimate goal to increase public mental health.

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Part IV
Key Concepts

Chapter 26
Defining Big Data

Andrea De Mauro

'Big Data' has shown to be a trending catchphrase that expresses the most promising trends in modern Information Technology. As of 2011, the term has increasingly permeated business readings and scholarly literature, quickly reaching the infamous status of a "hype" (Gandomi and Haider 2014; Vassakis et al. 2018). Nowadays, its current and potential applications spare no industry or research domain, impacting business and society unprecedentedly (Mayer-Schönberger and Cukier 2013). However, besides its extensive popularity, there is no complete consensus on its true definition, and it is easy to find different and diverging senses of the same term (Mikalef et al. 2017). This short paper defines the structural elements underlying the concept of Big Data, highlighting the features that make it different from conventional data.

Since the dawn of humanity, data has been the fundamental tool for recording and managing business exchanges, making it ubiquitous in any economic activity. As a consequence, firms have always leveraged data to support the functioning of their operating model. Therefore, it is hard to define a sharp cut between the traditional concept of data and the current utilization of Big Data. The literal meaning of the adjective 'Big' has led many to interpret the volume of data as its primary defining factor. However, given the continuous exponential growth of the world's technological capacity to store, communicate, and compute digital information (Hilbert and López 2011), one cannot set a static threshold of data volume. Hence, we shall ask ourselves, what makes Big Data 'Big,' and what set of features differentiate it versus the traditional data that has been consistently used to record economic transactions.

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_26

Table 26.1 Defining features of data in the pre- and post-Big Data era

Defining features	Pre-Big Data	Post-Big Data
Data volume	Stored locally or in centralized architectures	Disseminated in a remote and decentralized infrastructure (cloud)
Data velocity	Updated at a frequency comparable to the one of human transactions. Data usually change over days, weeks, months	Updated more frequently than usual human transactions. Data change in real-time
Data variety	Mainly structured data, organized in tables within relational databases	More unstructured data, including natural language, images, and videos, increasingly stored in non-relational databases
Analytical methods	Focus on summary statistics, aggregations, descriptive analytics	Focus on predictive and prescriptive analytics, powered by artificial intelligence
Source	Primarily from centralized entities such as firms, governments, science laboratories	Primarily from decentralized entities such as individuals and IoT devices
Primary business usage	Support of accounting, controlling, and human-driven decision making	Enabling machine-driven processes and automation of cognitive tasks
Primary strategic role	Support the operating model of a company or an institution: is a driver of incremental efficiency	Transform the organization's business model: is a source of competitive advantage or broader societal benefits

With the emergence of the Big Data phenomenon, some of the aspects describing the characteristics, the origin, the usage, and the role of data in firms have progressively become more prominent. Table 26.1 shows seven defining data features that collectively illustrate the fundamental changes developed as the Big Data phenomenon appeared.

Volume, Velocity, and Variety (generally referenced as the "three Vs" model) have been the usual trajectories used to explain the essential characteristics of Big Data assets. In fact, the extensive size, speed of change, and increasing unstructuredness of data sets require specific technology (such as cloud-based decentralized infrastructures) and analytical methods (primarily powered by artificial intelligence) for their transformation into value (De Mauro et al. 2016). Notably, size by itself is not sufficient to explain the impact of Big Data in enhancing firm performance (Ghasemaghaei and Calic 2020). In contrast, it certainly defines the storage and computing performance requirements of the supporting technology stack.

Another defining feature of Big Data is its sources: while in the past data was mainly generated by centralized entities, such as companies or public institutions, data originates today from a plethora of decentralized sources. Individuals generate an ever-increasing feed of data points through their continuous interaction with both the digital and the physical world. Businesses are forced to thoroughly rethink their ways of interacting with end-consumers and understanding their behavior (Erevelles et al. 2016). The extensive availability of sensor-enabled, connected objects (known as the Internet of Things, IoT) is an additional source of distributed information that accompanied the arrival of the Big Data phenomenon (Atzori et al. 2010; Marjani et al. 2017).

Lastly, Big Data has proven to intrinsically change the way companies compete, consistently enhancing business results when leveraged (Wamba et al. 2017; Ferraris et al. 2019). Especially when leveraged in conjunction with Artificial Intelligence, data has moved from having a supporting role (enabling accounting and operational effectiveness) to becoming a strategic source of competitive advantage and a core element of a firm's business model (Iansiti and Lakhani 2020; Sestino and De Mauro 2022).

The seven features presented in this paper provide a joint description of the novelties brought by the arrival of Big Data and explain the fundamental shifts observed versus the traditional utilization of data in private and public organizations. Interestingly, such transitions do not appear to have stopped and can be used in further research to anticipate the directional evolution of the role of data in business and society.

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Chapter 27
Defining Ecological Momentary Assessment

Ulrich W. Ebner-Priemer

Abstract For research in daily life, multiple terms have been used to describe a quite homogenous set of methodologies. These include, among others, Ecological Momentary Assessment, Ambulatory Assessment, Experience Sampling Method, real-time data capture, and digital phenotyping, just to name a few. Those daily life methods: (i) are characterized by the assessment of data in the real-world; (ii) focus on individuals' momentary states; (iii) are idiographic in focus and therefore enable, in combination with the repeated micro-longitudinal assessments, the examination of within-subject processes; (iv) are multimodal and can integrate psychological, physiological, and behavioural data from e-diaries, smartphone sensing and wearables; (v) allow to reveal and investigate setting- or context-specific relationships, and (vi) have the possibility to run real-time analyses.

For research in daily life, multiple terms have been used to describe a quite homogenous set of methodologies. These include, among others, Ecological Momentary Assessment (EMA; Stone and Shiffman 1994), Ambulatory Assessment (Fahrenberg and Myrtek 1996), Experience Sampling Method (ESM; Csikszentmihalyi and Larson 1987), real-time data capture (Stone et al. 2007), and digital phenotyping (Insel 2018), just to name a few. According to my understanding, which is in line with the definition of the respective international society (SAA: http://www.ambulatory-assessment.org), the different terms highlight more the different origins and ancestors than real distinctions in methodology. For those interested in the history of the development of these terms, we recommend a historical review (Wilhelm et al. 2011) delineating that at the end of the last century, research groups in Germany, the Netherlands and the US started developing innovative methods to assess individual experiences and behaviour in everyday life. Those roots can be differentiated, with ESM characterized by paper–pencil diaries and pagers, EMA using electronic diaries

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https://doi.org/10.1007/978-3-030-98546-2_27

(e-diaries) early on, digital phenotyping focusing on passive smartphone sensing, and Ambulatory Assessment having a strong focus on physiological and behavioural monitoring used since decades in internal medicine (e.g. ambulatory blood pressure monitoring) and movement sciences (accelerative devices). However, nowadays most terms are used to describe a broad set of tools to assess affective experiences, cognition, behaviour, and physiological processes in daily life (Mehl and Conner 2012).

Many features distinctly characterize those daily life methods from more traditional assessment approaches like retrospective questionnaires or laboratory-based techniques. They (i) are, first of all, characterized by the assessment of data in the real-world, increasing therewith the ecological validity and generalizability (real-life: Reis 2012); (ii) focus on individuals' momentary or very recent states therewith avoiding retrospective distortions (real-time: Schwarz 2012); (iii) are idiographic in focus and therefore enable, in combination with the repeated micro-longitudinal assessments, the examination of within-subject processes (like dynamics in emotional, behavioural, and psychophysiological systems) (Ebner-Priemer and Trull 2011); (iv) are multimodal and can integrate psychological, physiological, and behavioural data from e-diaries, smartphone sensing and wearables; and (v) allow to reveal and investigate setting- or context-specific relationships (Tost et al. 2019). Finally (vi) the possibility to run real-time analyses on the (scientific) wearables opens new and promising possibilities. These include the use of triggered e-diaries (Ebner-Priemer et al. 2013), which query about symptoms of interest during moments of interest (e.g., whenever a subject uses her lighter, she gets queried about her urge to smoke), to set up early warning systems (e.g., whenever a patient with bipolar disorder shows a decreased numbers of hours slept, more phone calls and more activity a diagnostic session is triggered to clarify an upcoming manic episode), and the use of EMA as an intervention strategy, then labelled as Ecological Momentary Interventions (EMI; Heron and Smyth 2010) or Just-in-Time Adaptive Interventions (JITAI; Nahum-Shani et al. 2015).

The two most often raised concerns regarding EMA are reactivity and compliance. The first refers to participants undergoing EMA altering their behaviour, whereas the latter speculates that EMA poses an immense burden, therefore increasing compliance systematically over time. Fortunately, empirical studies revealed findings regarding both concerns. Systematically manipulating the number of assessments per day (2 vs. 6 vs. 12 times) didn't reveal any signs of reactivity (Stone et al. 2003). In the same vein, studies with demanding time-based designs, like querying e-diary assessments every 15 min or having daily assessments over 12 months (365 days) (Ebner-Priemer et al. 2020), revealed excellent compliance.

Compared to more traditional assessments, like retrospective questionnaires, e-diaries come with a few additional challenges originating from the repeated assessments. Two of those should be highlighted in some detail. First, a so-called time-based design has to be defined, namely a strategy on how often and when assessments should be posed. Normally such a time-based design encompasses the total assessment period (e.g. a week or a month), the number of assessments, as well as the duration between assessments (like every hour). The most often used rule of thumb is that the sampling frequency should fit the dynamics of the phenomena interest (Ebner-Priemer and Sawitzki 2007). In other words, highly fluctuating phenomena (like affect) should be assessed with a higher sampling frequency, compared to psychological phenomena with lower dynamics (like personality traits). Unfortunately, the dynamic characteristics of most psychological phenomena are unknown. In such cases, starting in a pilot study with an oversampling (a too high sampling frequency) has been recommended. According to current publication guidelines (Trull and Ebner-Priemer 2020) the considerations and decisions regarding the time-based design should be reported in scientific manuscripts. The second challenge is to provide sound e-diary items. Surprisingly, reports on psychometric properties are still rare in this area. This can be partially explained by the fact that traditional theories do not apply. Compared to e.g. personality assessments, e-diary approaches are usually interested in the fluctuations of phenomena in daily life. Accordingly, the within-subject variance is not conceptualized as error, but is the variance of interest. When assessing affect over time, the main interest is not to get an overall estimate of the average affective state of a given person, but to understand how and why affect is fluctuating over time, discovering triggers, antecedents and regulation strategies. Accordingly, reliability must be understood as momentary reliability. Fortunately, theoretical and computational developments have gained tremendous progress during the last years, coming up with sound solutions for calculating momentary psychometric properties for e-diary approaches (Geldhof et al. 2014).

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Chapter 28
Defining Artificial Intelligence

Felix Lindner

Abstract Artificial Intelligence (AI) has grown to become a research area that provides key technologies relevant across many disciplines and applications. This chapter briefly outlines the history of AI. The main areas of today's AI research landscape are described and their relation to each other is pointed out.

28.1 The Foundation of AI

The 1956 Dartmouth Summer Research Project on Artificial Intelligence is widely considered as the founding event of artificial intelligence (AI) as a field of research. In their proposal, the workshop initiators McCarthy et al. (1955) hypothesize that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it", hence they wanted to work on how "machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves." Fig. 28.1 depicts the broad structure of today's research landscape of AI: Knowledge Representation and Reasoning (KRR) together with Machine Learning (ML) form the two core areas that investigate the foundations of AI systems. While KRR focuses on concepts, reasoning, and problem solving, the goal of ML is to make systems able to learn from data, form abstractions, and improve themselves. The use of language by machines, as a distinguishing part of intelligence, is investigated in the area of Natural-Language Processing (NLP), Computer Vision (CV) is concerned with the realization of visual perception within machines, and in Robotics, all the aforementioned areas culminate with the goal to engineer robots that exhibit intelligent behavior.

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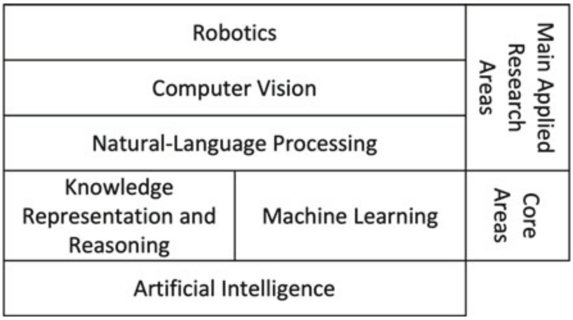
C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*,
Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_28

Fig. 28.1 Main research areas in artificial intelligence



28.2 Key Research Areas in AI

Knowledge Representation and Reasoning (KRR) formalizes the ability to conceptualize relevant aspects of the world and draw inferences about it. KRR has contributed to the goal of creating AI systems by developing various languages for formally representing knowledge and algorithmic procedures for drawing inferences from representations (see van Harmelen et al. 2007). The field maintains strong links to formal logic. Expert systems count as the main early developments of KRR. Beyond expert systems, KRR noteworthy contributions encompass formalisms for non-monotonic reasoning and methods for solving combinatorial problems in the service to action planning, spatial and temporal reasoning, and multi-agent systems.

Machine Learning (ML) develops algorithms for identifying patterns in big amount of data, and thereby forming abstractions for classification and regression tasks (see Bishop 2007). Learning tasks can be further sub-divided into learning from labeled data (Supervised Learning), identifying structures in unlabeled data (Unsupervised Learning), and learning from experience (Reinforcement Learning). A particularly successful approach to machine learning, which cuts across the three learning tasks, are Neural Network architectures, which are inspired by the functioning of neurons in the human brain. Recent advances in training multi-layer neural network have led to Deep Learning (Goodfellow et al. 2016) to become current state-of-the-art in machine learning. A shortcoming of neural architectures is the inexplicability of the resulting models. Logics-based rule-learning (Raedt 2011) is a machine-learning paradigm at the intersection to KRR and emphasizes explicability of the learnt models over accuracy.

Natural-Language Processing (NLP) enables machines to master natural-language understanding and generation (Jurafsky and Martin 2013). Both understanding and generation make use of techniques from KRR (e.g., translating texts to formal representations) and ML (e.g., finding patterns in huge amounts of text data). NLP has led to AI systems for tasks like question answering, machine translation, sentiment analysis, and chatbots.

Computer Vision (CV) investigates methods for automated understanding of image data (Szeliski 2021). The tasks of CV encompass object recognition and identification, motion tracking, and anomaly detection. Approaches to CV heavily rely on ML models to recognize patterns in the image data. The state-of-the-art is using Convolutional Neural Networks that render tedious feature engineering of earlier days unnecessary. For automated high-level interpretation of images also combinations with KRR methods are valuable, see Suchan et al. (2019). Applications of CV range from autonomous driving to medical diagnosis.

Robotics is the sub-field of AI dedicated to the goal of creating capable physical agents that can act in the real world (Siciliano and Khatib 2016). The realization of this vision requires a coherent integration of sensing technology (CV), solutions for learning from experiences (ML) and methods for reasoning about what is known about the world (KRR), and finally interfaces to communicate with humans (NLP). Robotics moreover adds specialized sub-areas that focus on real-time decision making such as robot locomotion and manipulation. Beyond AI, robotics research also overlaps with research areas such as engineering and dynamical systems theory.

28.3 Conclusions and Outlook

Artificial intelligence is a broad field of research that over the decades got split up into several sub-areas that focus on different aspects of making machines capable of solving problems that require some sort of intelligence. In the current public perception of AI, ML and Deep-Learning are most prominently represented. However, after several years of deep-learning research significant practical limitations of this approach become evident: The purely data-driven, correlative nature of current ML leads to biased AI models and a lack of explicability thereby hindering a wide deployment of AI systems into ethically sensitive areas such as medicine or law. In future, we will therefore witness a much stronger integration of methods developed in different areas of AI to better understand the mentioned problems and to eventually come up with socially acceptable solutions. Explainable AI (XAI), see Molnar (2022), is a recent research program dedicated to the goal of developing transparent, trustworthy, interpretable AI systems. It combines state-of-the-art ML methods with KRR methods for causal reasoning, abduction, and terminological reasoning. Human-in-the-loop learning (HL) is another research direction towards developing socially acceptable AI systems. HL directly integrates human feedback and advice for a learning system and therefore bears potential for increasing trust and safety of AI models (Amodei et al. 2016). Eventually, currently distinct AI research areas will increasingly interact to overcome the limitations of current systems, and the human factor will further gain importance both as a source of expertise for training more acceptable AI systems and more generally as an important factor in designing ethical AI systems that can be trusted.

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Chapter 29
Defining Machine Learning

Simon Hegelich

Machine learning is a dynamic concept that has been (and continues to be) developed and theorized from multiple perspectives within different disciplines. It defies attempts to arrive at a single fixed definition. When we talk about machine learning, we should consider at least three different standpoints: that of computer science, that of mathematics and that of its application to various problems. In general, we can say that it is a sub-field of artificial intelligence and increasingly the term is being used as a synonym for deep learning, which is a fast-growing sub-field of machine learning.

29.1 Machine Learning: Three Layers

When the term was first used in the late 1950s, the application perspective was predominant: Arthur Samuel, an IBM engineer, wrote a computer program that could learn to play the game of checkers and published an article about this machine learning application (Samuel 1959). Later, in the 1980s, machine learning was seen more as a general approach in the quest to create human like artificial intelligence. Michalski et al. (1983) wrote in the introduction to their famous book *Machine Learning: an artificial intelligence approach*: "The study and computer modeling of learning processes in their multiple manifestations constitute the subject matter of machine learning" (Michalski et al. 1983, 3). In the same volume, Herbert Simon (1983, 27) argues that machine learning has two goals: one, to overcome limitations in the human learning process and second, to simulate human learning in order to understand it better. It was Mitchell (1997, 2), who gave a more formal definition to

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Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_29

machine learning in the 1990s, following a switch of focus from applied psychology and artificial general intelligence towards statistics and applied computer science: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E." This formalization allows us to differentiate machine learning in three layers that can be described mathematically:

1. When we talk about machine learning today, it is assumed that we have a computer program or algorithm that is using a mathematical formula describing the task T. This is the machine learning model itself and there are many different choices on offer—from linear regression over support vector machines to neural networks.
2. The performance P is measured with a second mathematical formula: the cost-function. In most cases, the cost-function measures the differences between the already known values of some variables in the training data and the corresponding predictions that result from the model. This setting is called supervised learning because the training data already includes the "right" answers and the computer program is optimizing the model so that the output is closest to this ground truth. But even in an unsupervised learning setting, where there are no defined output variables the machine learning algorithm will still have a cost function. In clustering, for example, the computer might try to decrease the distance of observations within one cluster while increasing the distance between clusters.
3. The third part of a machine learning algorithm is the optimization part that models the experience E. The formula that represents the machine learning model has some (or nowadays trillions) unknown parameters that have to be altered in a way to minimize the cost-function. This job is done by the optimization algorithm.

29.2 Machine Learning: Three Perspectives

We can now explore the three different perspectives of mathematics, computer science and applied machine learning in more detail and link them to the three aforementioned layers.

1. The mathematical perspective on machine learning falls under the rubric of statistical learning. The fundamental assumption is that data is the result of some unknown data-generating process and mathematical models can be used to simulate this process. The results from the mathematical model (predictions) differ from the real-world data. This might be caused either by a sub-optimal model producing a systematic deviation (*bias*) or by the unpredictable errors that are part of the data-generating process (*variance*). The art of machine learning can be said to lie in choosing the right algorithm and the right test-methods to find a model that is closest to the data-generating process but can exclude or

minimize the noise inherent in the data. Of course, mathematicians are liable to be interested in all aspects of machine learning but the layer of the model (the mathematical formula) is central.

2. From a computer science perspective, the most important question is how to program a computer to do machine learning. Here, the focus is on the optimization algorithm. The model and the cost-function stay just as relevant of course, but computer scientists have to wonder if existing hardware is able to solve the equations in a reasonable time-span as different algorithms might behave very differently with large increases in the amount of data to be processed.
3. From an applied perspective, the models are often interchangeable, and the optimization algorithm is something deep under the hood that the computer does in the background. But the cost-function is central, because that's what defines what counts as a good result. Do I need a machine learning system that makes very good predictions or do I need a general model of a process to generate insights or even do inference? What is the data that goes in the model and what is the expected output? Political data science adds an additional dimension to the applied perspective: Large and growing parts of the political communication sphere nowadays, especially in social media, are manifestations of machine learning algorithms. Termed political machines (Papakyriakopoulos 2021), these are part of the political sphere and are of great interest to political scientists. Analyzing the underlying algorithms themselves as the object of study, and not simply as accepted statistical methods, shifts the attention again to the cost-function. The most relevant question in the political context is: What are these algorithms optimizing? We have for example seen a shift from optimizing the time spent on social networks to optimizing the number of interactions and this shift has radically changed political communication in social networks (Papakyriakopoulos et al. 2020).

29.3 Neural Networks

Increasingly, the term machine learning is being used synonymously for one special class of algorithms: neural networks. The three layers of machine learning algorithms and the three different perspectives can be used to explain this class of machine learning and to explain its popularity.

The model in a neural network is presented as a computational graph. Neurons (nodes) are organized in layers and (in a vanilla setting) all nodes from one layer are connected to all nodes from the next. Every connection from one node to another (edge) has a weight: a trainable parameter that regulates the importance of the edge. From a mathematical perspective this structure is very interesting because the whole neural network collapses to simple linear algebra operations. In the end, every step is a matrix multiplication and a variety of well-known transformations can be applied.

From a computer science perspective, the presentation in a computational graph makes a neural network quite easy to program because it is more structured than a mathematical equation. Applied machine learning experts are often fascinated by neural networks, because they are somehow supposed to mimic the human brain, but that is mostly a good PR-argument regarding the use of neural networks while treating them as a black box.

The cost-function of neural networks is extremely flexible. This class of algorithms can be used for nearly any problem from regression over classification to generation. The structure of the computational graph allows any number of response variables, even more than the input variables, in extreme cases. The cost-function measuring the performance is already plugged in when the model itself is defined, which increases the flexibility even more. The user can choose between squared-error or entropy functions, for example, to tweak a model to be more or less discriminative.

The optimization algorithm is the secret sauce for the success of neural networks. The procedure is called backpropagation (Werbos 1994). The neural network starts with random weights. This allows it to calculate a first prediction for every data point. Due to the inherent randomness, this prediction will be very bad, but this allows the network to calculate the derivatives and thereby find out in which direction each parameter should be altered. After applying very small changes on the parameters, the procedure is repeated many times until the model converges. The good thing about this procedure is that each computational operation is very simple. The bad thing is that you need millions of operations. This is the reason why neural networks became mainstream only when graphical processing units (GPUs) could be used to perform these operations in parallel.

29.4 From Neural Networks to Deep Learning

Deep learning has been described as simply the use of neural networks with many layers (Hegelich 2017) but this simplification misses the qualitative change in machine learning models. Although deep learning models are neural networks, they normally are not designed as fully connected layers. They include feedback loops and the data might be entered in a serial manner so that the network can learn patterns from the order of data and not only from its frequencies. The architecture of deep learning models gets more and more creative so that parts of the network take over quite different functions. A state-of-the-art deep learning network for example might map every data-point in a multidimensional vector-space, identify patterns in the structure of the data, encode this information in a new vector (with new dimensions) and train a decoder that is using this encoded information to solve some problem, again using different layers with loops and shortcuts. The result is a neural network that is a *black box*, not because the algorithm is a secret but because it has literally trillions of trainable parameters and nobody can tell exactly how it works. There are, in fact, no mathematical proofs for many aspects of this kind of architecture and the whole field is, at the moment, dominated by computer science. Progress is measured in setting up new records in well-known benchmark data-sets. A new model is considered better, simply because it performs better.

The cost-functions have not changed much from neural networks to deep learning, so this is still a good starting point to ask, what is optimized by the algorithm. But even this question gets more complicated because the newest deep learning algorithms integrate different goals in one cost-function (like generating artificial data and discriminating between original and artificial data, an architecture called Generative Adversarial Network GAN) or use reinforcement learning (the computer gains rewards instead of just minimizing the cost) for some parameters.

The optimization algorithm is still backpropagation (with more nuanced features like flexible learning rates, stochastic gradient decent, etc.). An important paradigm shift from neural networks to deep learning is *transfer learning*. Instead of training the model only on the data-set of interest, state-of-the-art deep learning models are pre-trained on huge data-sets often from different domains. A deep learning algorithm for medical image classification might be trained on YouTube videos first. This makes it very difficult to reproduce any results and to understand the behavior of these kind of algorithms. From a political perspective, accountability becomes more and more obscure, even in applied settings. Who is responsible in the end: the programmer or the company deploying the model, the architect developing the algorithm or the developing team that is tuning the parameters and training the model on out-of-domain data-sets?

29.5 Conclusion

Machine learning is a moving target. It is one of the most dynamic fields in science today and it is very likely that our understanding of machine learning will keep on evolving. Perhaps, we will see the mathematical perspective again gaining ground in the coming years. Or, we might witness a reunification of the old dream of artificial general intelligence and deep learning. Whatever the future might bring, scientists of all disciplines would do well to make themselves cognizant of the fact that machine learning is not only a powerful methodological tool to solve problems but is already a subject of study in its own right with myriad effects in the real-world—whether it is the effect of Facebook algorithms on psychological issues in teenagers or the effects of algorithmic trading on the stability of financial markets or the impact of social media on the increasing polarization in politics. Progress in research examining social phenomena driven by big data and the communication revolution depends, to varying extent, on continually updating scholarly understanding of the latest developments in machine learning algorithms.

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Chapter 30
Defining Privacy

Frank Kargl, Benjamin Erb, and Christoph Bösch

Privacy is a broad concept that relates to a variety of personal rights to keep personal matters secret from others. *Informational privacy* is a more focused notion of privacy that refers to the human right of informational self-determination. This means that individuals should be able to control when and to what extent their personal information is communicated to and shared with other parties. Privacy also encompasses an area of research that investigates how these rights are threatened, or in turn, how they can be protected, particularly through applying appropriate technical and organizational measures. *Data privacy*—the protection of personal data with certain *confidentiality* guarantees—is essential regarding digital technologies for applications in the study of human behavior.

According to Art. 4(1) of the GDPR , "*Personal data* are any information which are related to an identified or identifiable natural person." However, the exact legal scope of personal data slightly differs in different privacy regimes and legal frameworks (e.g., GDPR, HIPAA, CCPA). Specific pieces of information that are sufficient to identify a person or to be linked to an individual are also known as *personally identifiable information* (PII). Again, the legal scope of such PII may vary. Some definitions (e.g., NIST) distinguish between direct (linked) information and indirect (*linkable*) information. Examples for direct information include full names, dates of birth, passport numbers and other direct *identifiers* of a person. Indirect identifiers require additional knowledge and information for successful linkage to a person. For instance, the placement in an age group might become a *quasi-identifier*, given

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Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_30

there is only a single person of high age within the sample that can hence be linked. Notably, legal frameworks such as the GDPR also consider *technical PIIs* such as (personalized) cookies, device IDs, or IP addresses.

Privacy plays an important role also in empirical research studies. On the one hand, legal frameworks define and regulate the use of personal data for research purposes. Here, an *informed consent*—a freely given, specific, well-informed, and unambiguous indication that signifies agreement to the processing of personal data—is a common requirement for lawful data usage by researchers. On the other hand, in some regulations research constitutes a legitimate reason to process data without consent. Beyond regulatory compliance, there is also a *research-ethical obligation* of researchers to act *trustworthy* and protect the personal data of their participants and to maintain promised *confidentiality*—to prevent access to personal data by unauthorized parties or entities.

The GDPR defines a data life-cycle and the different parties involved in data handling. The *data life-cycle* includes collection, transfer, processing, storage, updating, retrieval, use, release, and deletion of data. The *data subject* is a natural person that has provided data with identifiable information (i.e., personal data). The *data controller* is the party that determines the purposes and means of the processing of personal data. Here, *data processing* includes any operation performed on personal data as part of the data life-cycle. The *data processor* is the party that conducts data processing on behalf of the data controller. For instance, when conducting an online survey with an external survey provider, the participants are data subjects, the researchers are data controllers and the survey provider becomes a data processor which requires a formal data processing agreement between both.

Anonymity is a condition that is provided if actions or pieces of information cannot be correlated with the specific identity of an individual. Anonymity can be achieved by removing PII from data, also known as *anonymization* or *de-identification*. After proper anonymization, the subjects included in a data set form an *anonymity set*—a group of subjects that cannot be distinguished from each other based on considered information. *Pseudonymization* is a weaker alternative to anonymization in which directly identifying characteristics are not removed, but replaced by *pseudonyms*. In this case, pseudonymous identifiers are used instead of the real names or other direct identifiers of subjects.

Essential anonymization techniques for research data sets with personal data include *suppression* (i.e., blinding of data items; e.g., removing a date of birth), *generalization* (i.e., reduction of data granularity; e.g., grouping dates of birth into buckets), or *adding noise* (i.e., randomizing data by a small amount; as e.g., done in differential privacy).

When data has been insufficiently anonymized or pseudonymized, attackers could be able to revert these actions. A successful attack can either decrease the level of anonymity (*de-anonymization*), or even recover actual identities (*re-identification*). Such attacks often rely on additional contextual information and/or secondary data against which the data under attack can be *linked*. For example, a data set which seemingly had been anonymized by removing names, addresses, and dates of birth could still retain a zip code and age per individual. The tuple of zip code and age might then constitute a quasi-identifier and be linked against other available information such as public voter records, effectively re-identifying at least some of the subjects.

For computing systems, privacy can be achieved by a variety of measures. A *privacy by design* approach takes privacy into account as an initial requirement and addresses it throughout the whole engineering process. *Privacy* or *data protection impact assessments* can help to identify privacy threats in a system during its design phase. *Privacy design strategies* and *privacy patterns* provide abstract concepts and proven best-practice solutions to support privacy in an IT system. When transitioning from system design to system implementation, *privacy engineering* provides processes, methodologies, and tools to implement privacy as a non-functional requirement. Throughout this process, *privacy-enhancing technologies (PETs)* can be utilized, to implement fundamental data protection principles, e.g., based on cryptographic mechanisms. *Privacy by default* is a property of an IT system where the default configurations are set to most privacy-friendly settings from the beginning so that a user would actively have to change them to weaker options if desired.

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Chapter 31
Defining Digital Biomarkers

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Recent years have seen a tremendous rise in the number of research projects investigating digital footprints to predict mental states and traits (Insel 2017; Marengo and Montag 2020; Markowetz et al. 2014). In the literature, often terms such as digital phenotyping or mobile sensing are used to describe this new scientific approach to sense psychological or other variables (e.g. psychiatric) either via a mobile device such as the smartphone (mobile sensing) or from digital footprints left from increased interactions with the Internet of Things (hence phenotyping a person based on his/her digital footprints; Baumeister and Montag 2019). In a recent paper by Montag et al. (2021a) the surprising observation has been made that although the psychological and psychiatric sciences have been early adopters of digital phenotyping and mobile sensing, the neurosciences so far only seldom applied such an approach, in detail trying to link the neurobiology of a person with his/her digital footprints. Such an endeavor without a doubt makes sense, with the current prevailing view that mind arises from matter (Cobb 2020).

Against this background, the present short chapter aims at a definition of the term "digital biomarker." From our perspective the term "digital biomarker" can be used either in a broader or more narrow sense. For instance, Dagum (2018) speaks in his work of a digital biomarker, when linking smartphone data to performance in

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C. Montag and H. Baumeister (eds.), *Digital Phenotyping and Mobile Sensing*, Studies in Neuroscience, Psychology and Behavioral Economics,
https://doi.org/10.1007/978-3-030-98546-2_31

neuropsychological tests. As it is well-known that individual differences in performance on neuropsychological tests can provide insights into individual differences in brain functions (Arlt et al. 2013; Fan et al. 2014; Seidman et al. 1994), one could therefore say that the work by Dagum (2018) indeed deals with digital biomarkers or digital brain biomarkers (at least indirectly; see also the work by Dagum 2019). Following such logic, one would probably also take into account that in general human behavior is a result of biology, as humans are biological systems. In this context, we clearly also want to mention that the view of humans being genetically determined is challenged by the many twin studies also showing the relevance of the environment to explain individual differences in human behavior and related psychological variables (Polderman et al. 2015). Hence, at least one has to take into account that the environment shapes the biological system, for instance via epigenetics (Montag and Hahn 2018; Sanwald et al. 2020).

With these points all made, researchers might therefore also want to use the term "digital biomarker" in a more restrictive way. We might expect that one would speak only of digital biomarkers when studies find support for a direct link between biological variables such as MRI data, hormone levels, genetic markers and digital footprints of a person left on a smartphone (including passively recorded data via sensors), wearables or social media for example. We would like to give some examples for such digital biomarkers. For instance, Huckins et al. (2019) observed a positive associations "between smartphone screen time (e.g., phone unlock duration) and resting-state functional connectivity (RSFC) between the subgenual cingulate cortex (sgCC), … and regions of the ventromedial/orbitofrontal cortex (OFC)" (p. 1). In their work more connectivity between the aforementioned brain regions was associated with increased use of the smartphone. Why could this be an example for the study of digital biomarkers in the narrow sense? From our perspective this is the case, as the smartphone behavior was digitally recorded (a digital footprint) and linked to a signal (MRI) itself giving direct insights into human biology. Another study using a comparable research set up, linked actual recorded Facebook behavior on the smartphone to gray matter volume of the nucleus accumbens (Montag et al. 2017). Whereas in the earlier example by Huckins et al. (2019) digital footprints were linked to resting state fMRI data, in the latter example by Montag et al. (2017) digital footprints were linked to structural MRI data. The logic is the same in the examples though, namely linking digital footprints "directly" to biological markers. Clearly also other examples illustrate the feasibility of combining smartphone-log-data with biological data. Given the brevity of this definition chapter, they cannot be reviewed here in detail (e.g. Duckrow et al., 2021; Gindrat et al., 2015; Sariyska et al. 2018; for a more detailed review see Montag et al., 2021a). This all said, the research field dealing with digital biomarkers is still in its infancy and several obstacles need to be overcome—such as defining thresholds of association strength between digital footprints and biological variables—to speak with some certainty of a digital biomarker.

In sum, in the narrow sense a digital biomarker describes a digital footprint (or a pattern of digital footprints) providing direct insights into the biology of a person, whereas in the broader sense such digital footprints might also be characterized as a digital biomarker when they are linked to variables such as test performance in a neuropsychological test, which in fact are known to be linked to biological variables. The latter would therefore be more of an indirect digital biomarker. Perhaps such a distinction is also helpful in the future, hence speaking of direct vs. indirect digital biomarkers (Montag et al. 2021b).

Of note, until now a few digital biomarkers have been carved out in the brain sciences with studies revealing direct links between digital footprints and the neurobiology of a person. Nevertheless, we are convinced that these kinds of studies and insights will rise in numbers very soon. Moreover, those medical sciences not focusing on the human brain in the future will more often study digital footprints to discover digital biomarkers for important health variables including high blood pressure, obesity and so forth.

Conflict of Interest Christian Montag mentions that he received funding from Mindstrong Health for a project on digital phenotyping. Beyond that he serves as scientific advisor for Applied Cognition, Redwood City, CA, USA. This activity is financially compensated. Paul Dagum is the founder of Mindstrong Health, a company developing digital phenotyping products for mental healthcare delivery. He served as its Chief Executive Officer from its founding in 2013 through October 2019 and was granted five U.S. patents on digital phenotyping and digital biomarkers. PD is currently co-founder and CEO of Applied Cognition developing diagnostic and therapeutic solutions for Alzheimer's disease. PD owns stock in Mindstrong Health and in Applied Cognition.

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